

Ability Level Differences in Learning Performance of Electrical and Electronic Technology Education Students in Virtual Reality Based Learning

A. Abdulaziz

abdulrazakabdulaziz28@gmail.com

Federal University of Technology Minna

A. E. Okonkwo-Umeh

Federal University of Technology Minna

T. M. Saba

Federal University of Technology Minna

O. A. Ojerinde

Federal University of Technology Minna

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Abstract

Virtual reality (VR) is gaining popularity as a tool in vocational and technical education due to its potential to provide immersive and interactive learning experiences. This study examined the ability levels of Electrical/Electronic Technology Education (EETE) students before and after they were exposed to VR-based learning in North Eastern Nigerian educational institutions. A quantitative technique with quasi-experimental and ex post facto components were used. The study included 62 NCE III EETE students from six Colleges of Education that were recruited via total population sampling. Students were divided into three ability levels: high, medium, and low. Pre-intervention classification was based on prior academic records, but post-intervention classification was based on assessment performance after VR-based learning. The data were analyzed using frequency counts and percentages. Prior to VR experience, 9 students (14.5%) were rated as high ability, 27 (43.5%) as medium ability, and 26 (41.9%) as low ability. Following VR exposure, 36 students (58.1%) were classified as high ability, 22 (35.5%) as medium ability, and 4 (6.5%) as low ability. The findings show a significant descriptive movement toward the high ability level, with commensurate decreases in the medium and low ability levels. The findings underscore VR-based learning's potential to improve learning performance, as well as the need of taking students' beginning ability levels into account when evaluating immersive learning settings.

Introduction

Virtual reality (VR) has progressed from a new computing technology to an increasingly researched teaching medium capable of creating interactive, computer-generated worlds in which students can watch, modify, and engage with virtual objects, processes, and surroundings. Depending on the technology, VR environments can use visual, aural, and haptic input to provide varied levels of immersion and interactivity (Elmqaddem, 2019; Long *et al.*, 2024). In addition to education, VR has been used in medical training, cultural heritage, sports, and language learning (Chong *et al.*, 2021; Richlan *et al.*, 2023). However, its instructional usefulness extends beyond the novelty of technology. VR can be used to portray phenomena, methods, and surroundings that would be difficult, expensive, dangerous, or prohibitive to recreate repeatedly in traditional instructional settings. This ability is especially important in engineering and technical education, where students are required to analyze three-dimensional structures, understand spatial relationships, visualise system functions, and build competence via the practice of technical procedures. Ka *et al.* (2025), for example, found that VR-based learning may deliver immersive learning experiences and help students connect with complicated three-dimensional engineering knowledge. As a result, virtual reality is increasingly viewed as a supplement to existing educational methods, rather than a replacement for them.

However, the evidence for VR's educational usefulness is more difficult than its technological attractiveness would suggest. The nature of the educational activity, the design of the virtual world, the degree of student interaction, and the students' characteristics may all influence the learning results connected with VR. According to research in science and engineering education, virtual reality (VR) can help students build practical skills and learning outcomes, especially when they need to conceptualize,

manipulate, and perform complex operations. Similarly, research in vocational and technical education reveals that immersive and mixed-reality technologies can improve cognitive, behavioral, and affective learning outcomes, albeit their efficacy may vary depending on instructional and contextual factors (Keller *et al.*, 2025). Rafiq *et al.* (2022) also found that VR-based learning in vocational higher education improved students' sense of presence, motivation, and engagement. Collectively, these studies establish VR's instructional potential while also emphasizing that its educational impacts should not be interpreted in isolation from the learning settings or the attributes that students bring to the learning environment.

Prior academic preparation is a student-related element that deserves special consideration. Students that enter technology-supported learning environments may not have the same amount of prior knowledge, conceptual understanding, or subject matter experience. These distinctions may affect how students perceive, process, and integrate information offered in immersive situations. Han *et al.* (2023) found that prior knowledge can alter the efficiency of instructional signals in an immersive VR learning environment. Their findings suggest that instructional support may not be the same for students with different amounts of prior knowledge. This implies that the efficacy of a VR learning environment cannot be considered to be uniform across students. Instead, variations in students' prior academic preparation may influence how they interact with and profit from immersive learning settings.

Another important student quality for VR-based learning is spatial competence. Immersive environments usually demand students to analyze three-dimensional representations, comprehend spatial relationships, control virtual objects, and mentally alter visual data. Brucker *et al.* (2024) emphasized the importance of visuospatial ability in immersive and desktop-based learning environments, suggesting that individual differences in spatial ability can be linked to variances in learning success. Similarly, Safadel & White (2020) discovered differences in spatial information processing among students with different levels of spatial ability and concluded that students with lower spatial ability may benefit more from VR than desktop-based learning in spatial recognition tasks. These findings are crucial to Electrical/Electronic Technology Education (EETE), in which students must evaluate circuit layouts, component arrangements, linkages, system structures, and other spatial interactions. As a result, learning differences must be considered while evaluating VR's instructional potential in technical education.

The link between student characteristics and VR learning outcomes, however, is not always consistent. Immersive learning may provide additional support for some students while increasing the demands on others. Wainman *et al.* (2021), for example, found that when learning anatomy through VR, students with lesser visuospatial abilities fared worse than students with greater visuospatial abilities, but the differences between the groups were less significant when physical models were employed. Such evidence suggests that the spatially rich and participatory aspect of VR can interact with students' pre-existing traits. As a result, the idea that VR inevitably gives equal learning gains to all students warrants empirical investigation. Understanding how students that join VR learning environment with different

levels of academic preparation perform later on can provide proof that overall mean achievement alone cannot.

This is particularly relevant in vocational and technical education, where learning necessitates the combination of theoretical knowledge with practical skills. Construction, woodworking, mechanical and vehicle technology, electrical technology, and electronics are examples of industrial technical education (ITE), in which students are intended to build both conceptual understanding and practical competencies (Orji, 2021). EETE focuses on teaching students to comprehend, install, maintain, troubleshoot, and repair electrical and electronic systems. Such preparation necessitates instructional methodologies that allow students to relate abstract concepts with actual applications and technical procedures (Ogbuanya & Chukwuedo, 2017; Orji, 2021). Technical and vocational education aims in Nigeria place a comparable emphasis on the development of practical abilities and readiness for constructive engagement in society and the economy (Federal Republic of Nigeria 2013). However, restrictions in training facilities, equipment, laboratory resources, and opportunities for repeated practical engagement may limit students' ability to learn these competencies through traditional methods alone.

The growing availability of digital technologies provides potential to supplement traditional practical education. Fitrihana (2023) stressed the role of digital technologies in vocational and technical education in promoting digital literacy, creativity, teamwork, and problem-solving. VR can be used in EETE to create simulated environments in which students can examine electrical and electronic systems, operate virtual components, investigate circuit designs, and rehearse specific techniques in a controlled setting. Such applications may supplement physical laboratory activities by providing additional chances for observation, investigation, and repeated practice, but virtual reality should not be considered a complete replacement for hands-on laboratory experience. Ezinma *et al.* (2024) observed constraints in the availability of quality training facilities for technical and vocational education and proposed virtual reality (VR) as a potential complementary way to increasing chances for practical learning. More recently, Bobboi *et al.* (2026) found that VR-based learning in EETE might assist active learning, keep students interested, facilitate communication, support the discovery of digital circuits, provide practical experiences, and provide instant feedback. These findings provide a foundation for further research into VR in EETE, while also posing an essential student-centered question: whether students entering VR-based education with different levels of academic preparation exhibit similar or dissimilar patterns of subsequent performance.

In the context of this study, the term Ability level needs to be carefully defined. Ability level is not used in this study to refer as spatial ability, prior knowledge, technical competence, IQ, or post-intervention achievement. Ability level is defined operationally as students' baseline academic achievement prior to exposure to VR-based training. Existing academic records are used to categorise students as high, medium, or low ability based on preset criteria. The post-intervention performance is then classified independently based on the applicable performance criteria. This distinction is significant because transitioning from one performance category to another after teaching should not be regarded as proof that a student's fundamental cognitive ability has shifted. Instead, it represents a shift in observed

performance classification under the settings of the learning intervention. The difference enables the study to investigate the distribution of students across predetermined baseline ability and subsequent performance categories without making unjustified claims about changes in underlying ability.

Existing research establishes foundation for investigating such differences. Evidence suggests that prior knowledge, visuospatial ability, and other student characteristics can influence how students process and respond to immersive learning environments (Han *et al.*, 2023; Brucker *et al.*, 2024). Kaba *et al.* (2024) have stressed the importance of student-related elements in assessing academic performance in technology-supported learning environments. These findings imply that relying merely on aggregate accomplishment scores may obscure important trends among students. For instance, a VR intervention may be associated with an overall improvement in accomplishment, but the size or distribution of that improvement varies among students accessing the intervention at different levels of academic preparedness. In contrast, the interactive and spatial qualities of VR may be especially beneficial to some students that struggle with traditional representations (Safadel & White, 2020). Examining performance distributions in respect to baseline ability can thus provide a more nuanced picture of VR-related learning outcomes. This student-centered approach has ramifications for instructional design. Effective virtual reality learning environments should do more than simply digitize traditional educational resources. They should give students the opportunity to explore, practise, receive feedback, and build understanding through meaningful engagement with simulated environments. Li *et al.* (2020) emphasized VR's experiential and participatory potential, while Han *et al.* (2023) indicated that educational support in immersive settings may need to account for variances in students' prior knowledge. As a result, understanding how students with different baseline performance levels are distributed across subsequent performance categories can be useful for designing instructional materials, determining appropriate scaffolding, and identifying students who may need additional instructional support.

Despite the growing data on VR in engineering, vocational, and technical education, there is a significant empirical gap in the distribution of learning outcomes across students entering immersive learning settings with different levels of academic preparedness. Existing research has investigated on the general effectiveness of VR, practical skills, motivation, engagement, spatial ability, and prior knowledge, while more recent research has shown that student characteristics can influence learning processes and outcomes in immersive environments (Han *et al.*, 2023; Brucker *et al.*, 2024; Yang *et al.*, 2024). However, there is limited evidence on how students grouped based on baseline academic performance are dispersed throughout subsequent performance categories after VR-based training in Electrical/Electronic Technology Education. The gap is thus not a general dearth of study on student differences in VR, but rather inadequate of context-specific evidence about ability-group performance patterns in EETE, notably in Nigerian colleges of education.

This distinction is significant in the Nigerian context because EETE students may enter teacher-education programmes with different levels of academic preparation and prior exposure to electrical and electronic principles. Although Nigerian studies have begun to investigate VR awareness and

applications in technical education, including the potential of VR to supplement practical training where conventional facilities are limited (Ezinma *et al.*, 2024), evidence on how students' baseline academic-performance levels correlate with their subsequent performance-category membership following VR-based instruction is limited. Examining this distribution is critical since aggregate mean scores alone may obscure whether students starting at different performance levels are represented differently following an instructional intervention.

As a result, this study investigates the distribution of Electrical/Electronic Technology Education students across established baseline academic-performance categories, as well as their subsequent performance categories following VR-based instruction in Northeast Nigerian educational colleges. In this study, the word ability level refers to students' baseline academic-performance classification based on existing academic records, rather than a direct test of general cognitive capacity, spatial ability, or intelligence. Instead of asserting that VR alters students' basic ability, the study focuses on visible patterns of performance-category membership. By evaluating these patterns, the study presents context-specific evidence that may help teacher educators and instructional designers understand how students with different levels of academic readiness are represented after VR-based learning.

Objectives of the Study

The study specifically seeks to:

- i. Determine the distribution of EETE students into high, medium, and low ability categories before VR-based education.
- ii. Determine the distribution of EETE students in high-, medium-, and low-performance categories after VR-based education.
- iii. Compare the distribution of EETE students across established ability/performance categories before and after VR-based instruction.

Theoretical Framework

The theoretical foundation of this study is Cognitive Load Theory (CLT), which provides a framework for explaining how working memory restrictions affect learning and why students may respond differentially to the same instructional setting. According to CLT, working memory has a limited capacity to process information, whereas long-term memory has a large store of knowledge organized into schemas that help integrate new information (Sweller, 2010; van Merriënboer & Sweller, 2005). Learning is thus more likely to be effective when instructional content is arranged in ways that allow students to concentrate their limited cognitive resources to processes important to understanding and schema development rather than needless processing demands. From this perspective, instructional success is determined not only by the content delivered, but also by the complexity of the learning task, the arrangement of instructional information, and the knowledge that students already possess.

CLT is especially important for VR learning because immersive environments can provide students with visual representations, spatial information, animations, noises, interactive objects, and procedural knowledge all at the same time. Although these elements can promote engagement and create possibilities for experiential learning, they may also increase the quantity of information that students must focus on and digest. CLT distinguishes between intrinsic cognitive load, which is caused by the inherent complexity and interactivity of the learning material, extraneous cognitive load, which is caused by the manner in which information or instructional activities are presented, and cognitive resources devoted to learning and schema development. As a result, the educational benefits of VR may be dependent in part on whether the virtual environment facilitates relevant processing without imposing excessive cognitive demands. This theoretical approach is significant in EETE because students may be expected to evaluate circuit configurations, component interactions, system operations, and procedural sequences in a three-dimensional environment.

Empirical evidence demonstrates the importance of cognitive load issues in immersive learning. Makransky et al. (2019), for example, found that students learning in immersive VR had a better sensation of presence but also had higher cognitive load and poorer learning results than students in a less immersive computer-based environment. This finding demonstrates that increased immersion does not always translate into improved learning, and it implies that the additional information and interaction associated with immersive environments may impose cognitive demands that can interfere with learning if not properly managed. Similarly, Moon and Ryu (2021) shown that instructional signaling can influence learning in immersive video settings, implying that adequate guidance may assist students in directing attention to relevant material. Skulmowski & Rey (2020) also claimed that highly realistic learning environments may present additional information for students to comprehend, thereby increasing cognitive demands. Petersen et al. (2022) have found that elements of virtual worlds and student interaction can alter the cognitive demands of immersive learning. Collectively, these studies show that the success of VR is determined not just by the availability of immersive technology, but also by the link between the properties of the virtual environment, instructional design, and students' processing resources.

Student qualities are especially relevant in this theoretical perspective. Students do not enter VR-based learning environments with the same level of prior knowledge, academic preparation, or subject matter experience. Prior knowledge can influence how easily new information is organized and integrated into current schemas, hence altering the cognitive resources available for processing new instructional material. Han et al. (2023), for example, discovered that students' past knowledge affected the efficiency of instructional signals in an immersive VR learning environment. Such findings indicate that instructional support may have various effects on students with different amounts of prior knowledge. Furthermore, research on visuospatial ability suggests that individual differences in students' ability to interpret spatial information can affect performance in immersive learning settings (Brucker et al., 2024; Safadel & White, 2020). These findings are especially pertinent to EETE, which requires students to evaluate circuit layouts, component arrangements, linkages, system structures, and other spatial interconnections.

In this study, however, ability level is not considered a direct indicator of general cognitive capacity, intellect, or visuospatial aptitude. Rather, it is operationally defined as a student's baseline academic performance classification based on existing academic records prior to VR-based training. This distinction is significant because baseline academic performance may reflect disparities in individuals' prior academic preparation and subject-matter knowledge while not necessarily reflecting their underlying cognitive ability. CLT provides a theoretical foundation for understanding why such disparities in prior preparation may result in diverse responses to the identical VR learning environment. Students that enter the learning environment with different levels of relevant knowledge may differ in their capacity to connect new material with existing schemas, as well as the cognitive resources available to absorb complicated instructional information.

As a result, CLT gives a theoretical explanation for the likelihood that students grouped into distinct baseline performance levels will exhibit varied patterns of performance after VR-based education. It does not, however, imply that student in the high, medium, and low baseline groups will necessarily have different post-intervention outcomes. Rather, it implies that prior knowledge and student characteristics may influence how instructional information is absorbed in a cognitively demanding setting. Thus, the hypothesis provides a foundation for empirically investigating whether students with different baseline academic performance levels exhibit various patterns of post-VR performance in EETE.

The use of CLT in the current study is not predicated on the idea that VR intrinsically increases or decreases cognitive burden, nor is cognitive load directly measured. Instead, CLT provides an explanatory framework for understanding why students with different levels of academic preparation may display diverse performance patterns when exposed to the same immersive teaching environment. As a result, the study broadens the use of CLT to VR-supported Electrical/Electronic Technology Education by investigating whether students' baseline performance classifications match their future performance-category distributions after VR-based education. This perspective can help to develop VR learning environments that provide adequate instructional support and scaffolding for students entering technical school with different levels of academic preparation.

Methodology

3.1 Design of the study

This study employed a quantitative research design that includes quasi-experimental and ex post facto methodologies to evaluate differences in learning performance among EETE students with high, medium, and low ability levels in VR-based learning environments. Students' initial ability levels were determined using previously recorded academic assessment results before to the VR intervention, and pre- and post-test assessments were utilized to detect changes in their learning performance following the intervention. The students' initial ability levels were determined using existing records, and the VR intervention was used to track how their learning progressed over time. Prior to implementing VR learning, students were divided into three ability groups based on their prior academic performance:

high, medium, and low. The students were retested following the VR session to see if their ability levels had changed from before the intervention.

3.2 Area of the Study

The investigation was conducted in Nigeria's northeast. The region has six states: Adamawa, Bauchi, Borno, Gombe, Taraba, and Yobe. The Northeast is a huge region in Nigeria's northern part. It has borders with Niger to the north, Chad to the northeast, and Cameroon to the east. The study looked at six local colleges that offer Electrical/Electronic Technology (EET) education programmes and NCE awards. Some of these institutions include the Federal College of Education (Technical) in Potiskum, Yobe State; the Federal College of Education (Technical) in Gombe, Gombe State; the College of Education (Technical) in Zing, Taraba State; the College of Education in Hong, Adamawa State; the Abubakar Tatari Ali Polytechnic in Bauchi State; and the Ramat Polytechnic in Maiduguri, Borno. Participants were eligible if they were enrolled in the NCE III Electrical or Electronic Technology Education program at any of the participating schools, could complete the Virtual Reality (VR) learning activity and the required tests, and had a prior academic record demonstrating their beginning ability level. Students were not eligible to participate in the study if they were not enrolled in the NCE III EET program, did not have the necessary academic background, or were unable to participate in the intervention and evaluation activities.

The study area and participants were carefully chosen since the specified universities provide NCE-level technical programmes in Electrical and Electronic Technology that teach students both theoretical and practical skills. NCE III students were regarded ideal candidates because they had completed the curriculum and understood the EET's fundamental and intermediate components. This helped determine how diverse their starting skills were prior to applying VR learning. The study allowed researchers to look at how students of different ability levels fared in a virtual reality learning environment. The findings may provide important real-world examples for educators to consider students' ability levels while using virtual reality to teach technical and vocational courses.

3.3 Population and Sampling Technique

This study employed a Total Population Sampling (TPS) technique. According to Kisanga (2026), TPS is a form of sampling process that is similar to a census but is not dependent on probability. This method invites all members of a given group that were available to participate. This method works best for a limited target group with specialised needs that is easily accessible. The study included 62 NCE III EETE students from the six designated NCE-awarding institutions. The study included all 62 students that met the criteria because the population was small and easily accessible. As a result, rather than focusing on a subset of the population, this study covered everyone that could be reached. The findings were interpreted in the context of the unique community under study and cannot be extrapolated to other similar locations or conditions.

3.5 Instrument for data collection

The study's main data sources were the students' academic records and previous exam scores, as well as the results of the post-intervention assessment. Existing school data from prior to the VR intervention revealed the children's performance in their normal courses. Using this information, we calculated the students' initial competence levels. Following classification, the students took part in educational activities that used EETE's virtual reality support. Following the VR intervention, students were given a follow-up exam, and the results were utilized to determine their ability levels. Because the study attempted to determine the students' true academic standing prior to the intervention without affecting or influencing their earlier learning experiences, using their current academic records was the proper decision. It was critical to assess students' performance after the intervention in order to acquire similar results revealing how well they fared after using VR.

3.6 Procedure for Ability-Level Classification

Two approaches were used to identify the student ability levels. The first step in establishing how well children fared in a typical learning environment was to review their test results and school records. Using the study's unique standards, the students were split into three groups based on their competency level: high, medium, and low. During the second phase of EETE, students engaged in virtual reality-based learning activities. Following the intervention, a follow-up examination was conducted, and the same approach was used to categorize the children into three ability groups: high, medium, and low. The changes in students' ability levels between the pre-intervention and post-intervention stages were investigated to determine if they advanced from Low to Medium or High, Medium to High, remained in the same ability category, or decreased to a lower ability level as a result of VR-based learning.

3.6. Data Analysis

The information from the students' previous test results and the tests taken following the intervention was coded and analyzed with IBM SPSS Statistics. Descriptive statistics, such as how frequently each category occurred and the proportion of students in each, were used to demonstrate how students were distributed across the High, Medium, and Low ability groups before and after the VR intervention. The manner in which students transitioned between ability groups was also investigated to understand how their skills evolved over time. Because the outcome was based on ability groups, a chi-square test was used to see if there was a significant difference between how children were classified before and after the intervention.

3.7. Ability-Level Interpretation

The students' ability levels were classified into three groups: high, medium, and poor. The starting ability level indicated where the children had previously stood intellectually, based on previous exam scores and school records under typical learning conditions. The ability level following the intervention indicated where they stood academically after adopting VR learning. When a student advanced from low to medium or high ability, or from medium to high ability, there was an improvement. Students that stayed in the same group were predicted to keep their ability level, but switching from a better to a poorer group resulted in a loss of ability. The approach divided students into three categories to make it easier and

more instructive to grasp the distinctions between students of different academic achievement. Instead of concentrating just on average results, the study could determine whether VR learning benefited students with different skills.

Despite the fact that virtual reality (VR) is becoming increasingly popular in STEM education, little emphasis has been placed on its use in EETE. There has been little research on how virtual reality might help students comprehend difficult topics like waveform interpretation, circuit analysis, and logic. When determining how effectively students do in virtual reality environments, it is vital to examine their ability level because what they already know influences how they absorb new concepts, see objects, focus their attention, and make sense of their surroundings. It is important to note that a person's ability level is generally seen as a critical aspect in how well they learn when using technology. This shows how different people process information, understand concepts, and participate in learning activities. Previous study has demonstrated that students' skills and grades differ between school contexts, implying that a student's basic aptitude level may influence how well they use and benefit from virtual reality learning spaces.

Students do not all enter technology-based learning environments with the same amount of knowledge, abilities, or academic aptitude. These variations can influence how students interact with and benefit from virtual reality training. According to the research, a student's ability level effects how they process visual and interactive knowledge, particularly in three-dimensional models. For example, one study found that students with low spatial abilities experienced higher mental strain in traditional learning environments, but that adopting VR reduced their mental strain and improved their learning. The study also discovered that students with good spatial abilities did not improve significantly, supporting the theory that existing strengths can assist compensate for other deficits. As a result, it is now a hot topic in educational research to study how virtual reality might help students of all abilities learn more effectively. Virtual reality allows students to inspect objects, comprehend processes, and explore locations that would be difficult to depict using traditional instructional approaches. Previous research shown that students with a weaker comprehension of spatial relationships benefited more from desktop virtual reality learning environments than those with exceptional spatial abilities. This demonstrates how virtual reality can assist students with restricted abilities by providing additional support. Nonetheless, the conclusions from different studies are inconsistent. According to one viewpoint, technology-rich learning environments benefit those who are less skilled, while another contends that advanced and interactive learning materials benefit those who are already proficient.

According to recent studies, further research is needed to determine how students' prior experience and ability levels affect outcomes in VR-based learning. One research of students with different levels of spatial ability in a desktop virtual reality environment discovered that students' thinking and behavioral reactions differed, despite the fact that individuals with both high and poor spatial abilities had similar learning outcomes. As a result, the authors emphasized the lack of evidence on how virtual learning environments may effectively serve students of various abilities. Similarly, a recent assessment of VR research found that students' initial aptitude levels are a crucial feature to consider when assessing the

effectiveness of VR-based learning. Despite these findings, most contemporary studies in vocational and technical education focus on spatial abilities rather than students' overall academic abilities. There has been little research into how students with various starting abilities succeed when learning EET via VR. This is an important area for further research because EETE requires students to understand abstract concepts, how circuits work together, various electronic parts, hands-on approaches, and lab activities that can be demonstrated and managed effectively in immersive virtual environments. As a result, VR works differently for each person, especially if their previous academic performance is not comparable.

This study is crucial because there is limited evidence available on how different ability levels affect learning thru VR-supported EETE. Some studies show how spatial abilities and virtual reality work, but the results are not directly applicable to students learning EET or categorizing people based on academic performance. Furthermore, the absence of clear data on whether VR aids students with lower abilities or improves the performance of those with higher abilities indicates that this link warrants further exploration in specific teaching situations. Examining how well students learn based on their beginning ability levels might assist establish whether virtual reality teaching provides the same or different effects for students with different abilities.

This study looks into how different levels of ability affect the learning performance of EETE students that were taught via virtual reality. The findings were expected to provide additional information to what we already know about virtual reality by offering real-world examples from vocational and technical education, as well as assessing whether students of all ability levels benefit equally from learning using virtual reality. This type of evidence can assist teachers, course developers, and lesson designers in determining if VR should be used as a standard teaching method for all students or if it should be customized to meet each student's unique starting skills.

After categorizing the students into High, Medium, and Low ability groups based on their previous exam scores and school records, the researchers presented a Virtual Reality (VR) learning software for qualifying NCE III Electrical/Electronic Technology students. The intervention used the same Electrical/Electronic Technology content for everyone and was completed in the same amount of time and instruction period.

Ability	Initial	Post	Interpretation
High	9 (14.5%)	36 (58.1%)	Significant increase
Medium	27 (43.5%)	22 (35.5%)	Decreased
Low	26 (41.9%)	4 (6.5%)	Decreased markedly
Total	62 (100%)	62 (100%)	Shifted toward higher classes

The results show a substantial shift in students' ability classifications following the VR intervention. The proportion classified as high ability increased from 9 (14.5%) at the initial classification to 36 (58.1%) post-intervention. Conversely, the medium-ability group decreased from 27 (43.5%) to 22 (35.5%), while

the low-ability group decreased from 26 (41.9%) to 4 (6.5%). Thus, the post-intervention distribution indicates an overall movement toward higher ability classifications.

4.1 Ability Levels of Students Prior to Virtual Reality Learning

The first research question investigated the ability levels of EETE students before they were exposed to virtual reality (VR)-based learning. The 62 NCE III EETE students were divided into three ability categories based on their baseline academic records, which were taken from existing school records under ordinary instructional conditions. The classification was used to determine the distribution of students' ability levels prior to the introduction of VR-based learning activities and to give a foundation for defining the distribution observed following the intervention.

Table 4.1

Student Distribution by Ability Level Prior to Virtual Reality Learning

Ability Level	Frequency (N)	Percentage (%)
High	9	14.5
Medium	27	43.5
Low	26	41.9
Total	62	100.0
Note. Percentages were calculated using the total sample of 62 students.		

Table 4.1 shows that 9 students (14.5%) were classified as high ability, 27 students (43.5%) as medium ability, and 26 students (41.9%) as low ability. The medium ability level represented the greatest proportion of students, followed by the low ability level, while the high ability level represented the smallest proportion. Overall, 53 students (85.5%) were classed as medium or low ability, with 9 (14.5%) classified as high ability. This distribution demonstrates that the students began the study with varying levels of past academic aptitude. Such diversity is important when looking at learning outcomes in VR environments because variances in prior knowledge and learner characteristics might influence how students interact with and benefit from immersive learning environments. Alazmi & Alemtairy (2024) found that past knowledge can influence students' navigation, task completion, perceptions, and learning experiences in VR-based learning. Similarly, Kaba et al. (2024) found differences in academic achievement based on students' majors, whereas Brucker et al. (2024) emphasized the importance of spatial abilities and perspective taking in virtual environments.

The baseline distribution also gives valuable context for interpreting the subsequent findings. Sun et al. (2019) observed that VR could reduce mental strain and aid learners with poorer spatial abilities, whereas Johnson et al. (2022) discovered that spatial ability influenced performance during VR-based training. Bödding et al. (2025) found that mixed reality technology can improve cognitive, behavioral, and affective learning outcomes in vocational education after conducting a systematic review of 53 studies.

These findings imply that differences in learner characteristics are important for assessing outcomes linked with immersive learning technologies. Thus, Table 4.1 depicts the dispersion of students' abilities prior to exposure to VR-based learning. The frequencies and percentages are descriptive and should not be regarded as evidence of the effectiveness of VR-based learning.

4.2 Ability Levels of Students After Exposure to Virtual Reality Learning

The second research question investigated EETE students' competence levels following exposure to VR-based learning. Following their involvement in the VR learning activities, the 62 students took the post-intervention evaluation, and their scores were classified as high, medium, or low ability levels using the predefined classification criteria. The resulting distribution is shown in Table 4.2.

Distribution of Students According to Ability Level After Exposure to Virtual Reality Learning

Ability Level	Frequency (N)	Percentage (%)
High	36	58.1
Medium	22	35.5
Low	4	6.5
Total	62	100.0
<i>Note. Percentages were calculated using the total sample of 62 students.</i>		

According to Table 4.2, 36 students (58.1%) were classified as high ability, 22 students (35.5%) as medium ability, and 4 students (6.5%) as low ability following exposure to VR-based learning. As a result, the students with the highest ability levels comprised the largest share, while those with the lowest ability levels constituted the smallest part. Compared to the baseline distribution in Table 4.1, the proportion of students classified as high ability grew from 14.5% to 58.1%, a 43.6 percentage point increase. The proportion classed as medium ability declined from 43.5% to 35.5%, and the proportion classified as low ability decreased from 41.9% to 6.5%. Descriptively, the distribution of students' ability levels following VR-based learning was more concentrated in the high ability category than before the intervention.

The observed distribution is consistent with earlier research demonstrating that VR and related immersive technologies have the potential to help people learn. Liu et al. (2020, 2022) found that VR had a favorable impact on students' learning outcomes, whereas Ragan et al. (2015) proposed that well-designed VR experiences with appropriate interaction components can help students engage. Calvert & Abadia (2020) have reported that immersive VR can improve student performance, engagement, and learning experiences. According to Ziyang & Nasri (2025), virtual reality can help students acquire and apply practical skills in vocational and technical education. Long et al. (2024) discovered that virtual reality-based virtual laboratories can help students improve their motivation, engagement, knowledge,

and practical skills in electrical and electronic engineering. AlFajrani et al. (2026) indicated that VR has the ability to provide realistic and safe practice environments while also promoting skill development and retention. These findings give useful contextual evidence for investigating VR-based learning in EETE.

However, the distribution in Table 4.2 should be read descriptively. The increased proportion of students identified as high ability following exposure to VR-based learning does not, by itself, prove that VR caused the observed shift. Because the same students were evaluated before and after the intervention, evaluating whether the change was statistically significant necessitates an analysis that takes into account the paired character of the observations. Individual student data are thus required for determining the extent to which students remained in or moved between the three ability levels.

4.3 Difference in Students' Ability Levels Before and After Exposure to Virtual Reality Learning

The third research question investigated the difference in the distribution of EETE students' ability levels before and after exposure to VR-based learning. The same 62 students participated in the analysis. The pre-intervention classification was based on students' baseline academic records, whereas the post-intervention classification was based on the assessment given following exposure to VR-based learning. Table 4.3 presents a descriptive comparison of the two distributions.

Table 4.3

Comparison of Students' Ability Levels Before and After Exposure to Virtual Reality Learning

Ability Level	Before VR N	Before VR %	After VR N	After VR %	Difference in N
High	9	14.5	36	58.1	+ 27
Medium	27	43.5	22	35.5	-5
Low	26	41.9	4	6.5	-22
Total	62	100.0	62	100.0	0

Note. Percentages were calculated using the total sample of 62 students. Difference in N represents the difference between the post intervention and pre intervention frequencies and does not represent the number of individual students that changed ability level.

Table 4.3 shows a noticeable descriptive shift in the distribution of students' abilities between the two measurement points. The number of students classified as high ability grew from 9 (14.5%) prior to exposure to VR-based learning to 36 (58.1%) post-exposure, reflecting a 27-student and 43.6 percentage point increase. The number of students classed as medium ability declined from 27 (43.5%) to 22 (35.5%), reflecting a drop of 5 students and 8.0 percentage points. Similarly, the number of students classified as low ability dropped from 26 (41.9%) to 4 (6.5%), a decline of 22 students and 35.4 percentage points. The overall descriptive pattern thus implies a shift in the distribution toward high ability levels as a result of VR-based learning exposure.

This descriptive pattern is essentially consistent with earlier studies on immersive technologies in technical and vocational education. Yang et al. (2024) found beneficial impacts of VR-based learning in experimental and quasi-experimental research, including a small positive effect on technical skill development among science and engineering students ($SMD = 0.363$). Chiang et al. (2022) observed that virtual and augmented reality applications can help with occupational learning and performance, whereas Asham et al. (2023) discovered that VR and AR applications can improve teaching and learning chances in electrical engineering education. AlFajrani et al. (2026) emphasized the potential of VR-based training while recognizing the need for more research on long-term impacts, skill transfer, knowledge retention, and performance. Although these studies provide contextual support for the current findings, differences in participants, interventions, research designs, and outcome measures should be taken into account when comparing the results to those of the current investigation.

It is important to note that the variations in Table 4.3 reflect differences in aggregate frequencies rather than individual student moves between skill groups. For example, the addition of 27 students to the high ability category does not imply that 27 students formerly classed as medium or low ability moved into the high category. Similarly, the drop of 22 students from the low ability category does not imply that all 22 students moved up to a higher category. Individual students' movements can only be determined using matching student level data that includes each student's ability classification before and after exposure to VR-based learning.

A transition matrix can thus be used to display the individual level mobility of students between the three ability levels. Such a matrix would show how many students remained at the high, medium, or low level, as well as how many migrated from one level to the next. This analysis would yield data that cannot be acquired from the aggregate frequencies shown in Table 4.3. If the research goal is to evaluate whether the distribution of ability levels has changed statistically, the matched observations should be subjected to an appropriate inferential approach for paired categorical data.

The findings should also be interpreted in light of the methodology used to create ability levels. The pre-intervention classification was generated from existing academic records, whereas the post-intervention classification was established from assessment findings received following VR-based learning activities. As a result, the findings should be viewed as a shift in the distribution of classified ability levels rather than conclusive proof of a change in an underlying, stable ability trait. If the same categorization criteria were used consistently on the underlying scores at both measurement sites, the comparison provides a useful description of the observed distribution. However, the various sources of the underlying scores should be recognized as a constraint when assessing the amount of the change.

Overall, the results show a significant descriptive shift in the distribution of students' ability levels after exposure to VR-based learning. The proportion labeled as high ability improved from 14.5% prior to the intervention to 58.1% post-intervention, whereas the proportion classed as poor ability declined from 41.9% to 6.5%. The pattern is consistent with findings that VR and related immersive technologies can enhance learning in technical, vocational, and engineering education. However, the current descriptive

findings should not be construed as evidence that VR-based learning caused the observed shift. Evidence of statistical significance and actual movement between ability levels should be established utilizing matched student level data and an appropriate inferential methodology.

4.4. Recommendation for Future Studies

The goal of this study was to look at how Virtual Reality (VR)-based learning performance varied across ability levels among EETE students in colleges of education. The study included 62 NCE III EETE students from six Northeast Nigerian colleges. The results revealed a significant descriptive shift in the distribution of students across ability categories following exposure to VR-based learning, with the proportion classified as high ability increasing from 14.5% before the intervention to 58.1% after the intervention, while the proportion classified as low ability decreased from 41.9% to 6.5%. These changes, however, should not be construed as conclusive evidence that VR caused the observed variations, as the research relied on aggregate ability-level distributions drawn from previous academic records and post-intervention assessment findings. The study also did not look into other student qualities that could affect VR learning performance, such as prior technical knowledge, spatial ability, technological competence, motivation, and learning preferences. Future research should investigate how these student characteristics interact with ability levels in VR-supported EETE learning, as well as use individual-level paired analyzes, larger samples, and participants from diverse geographical regions and educational levels to provide stronger evidence of VR-based learning's effectiveness for students with different levels of prior performance.

Conclusion

VR has increased in popularity as an educational tool due to its immersive and interactive features, which allow students to participate with both simulated and real-world learning environments. Virtual reality (VR) can aid in repeated practice, practical learning, interaction with virtual equipment, and technical idea visualisation in Electrical and Electronics Technology Education (EETE). The findings of this study demonstrated a considerable descriptive shift in the distribution of students across ability groups after exposure to VR-based learning. Prior to the intervention, 26 students (41.9%) were classified as low ability, 27 (43.5%) as medium ability, and 9 (14.5%) as highly capable. Following VR-based learning, 36 students (58.1%) were categorized as high ability, 22 (35.5%) as medium ability, and four (6.5%) as low ability.

As a result of exposure to VR-based learning, the data show a positive change in the overall distribution of student toward high-ability. However, because the aggregate frequencies show no individual movement across ability groups, this descriptive change should not be interpreted as evidence that VR caused the observed differences. The findings suggest that VR-supported learning could help EETE students visualise, interact with, and apply technical concepts in simulated environments that supplement traditional teaching. More study with individual-level paired data, appropriate comparison groups, and larger samples is needed to assess how much VR enhances learning performance among students with varied levels of prior ability.

Declarations

AVAILABLE DATA

The data supporting the study's conclusions came from the participating students' pre-existing academic records for the initial ability-level assessment, as well as exam scores obtained after the students were exposed to virtual reality. The researchers were able to analyze the data in accordance with institutional regulations and study protocols. Because it contains students' academic data and potentially identifying educational records, the whole individual-level dataset is not publicly available. The paper offers aggregated data supporting the findings, and the accompanying author may give more data upon reasonable request, in accordance with institutional and ethical norms.

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Author Contributions

The Contributor Roles Taxonomy (CRediT) is used in this publication to acknowledge individual author contributions, reduce authorship conflicts, and promote collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Abdulrazak	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Umeh	✓	✓		✓	✓	✓	✓	✓	✓	✓	✓		✓	
Saba	✓	✓		✓	✓	✓		✓	✓	✓	✓			
Ojerinde		✓		✓	✓	✓			✓	✓		✓		

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

Funding

This study received no external funding. The author's personal resources were employed for the research.

Accordance with ethical guidelines

The ethical standards and regulations of the approving institution, as well as the Declaration of Helsinki principles, were followed in all procedures involving human participants in this study. The protocols of the study guaranteed the participation of participants, their privacy, confidentiality, and anonymity, as well as their informed consent.

Ethical approval

This study involving human participants was reviewed and approved by the Research Ethics Committee of the Federal University of Technology, Minna, Niger State. The study was conducted in accordance with the relevant institutional ethical guidelines and applicable ethical standards governing research involving human participants. All procedures were carried out with due consideration for participants' informed consent, privacy, confidentiality, and anonymity.

Consent to Participate

Informed consent was obtained from all individuals in advance of the study. Participants were fully informed about the study's purpose and procedures, and their participation was entirely voluntary. Those who participated in the study were given notice that they could withdraw from the program at any point without penalty. Throughout the study, the participants were kept anonymous and kept private.

Consent to Publish

Not applicable. The manuscript does not contain any personally identifiable information, including images, photographs, videos or other items of individual participants.

Conflict of Interest Statement

According to the authors, there are no conflicts of interest with this study

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Figures

STUDY PARTICIPANT SELECTION FLOWCHART

NCE III INDUSTRIAL TECHNICAL EDUCATION STUDENTS

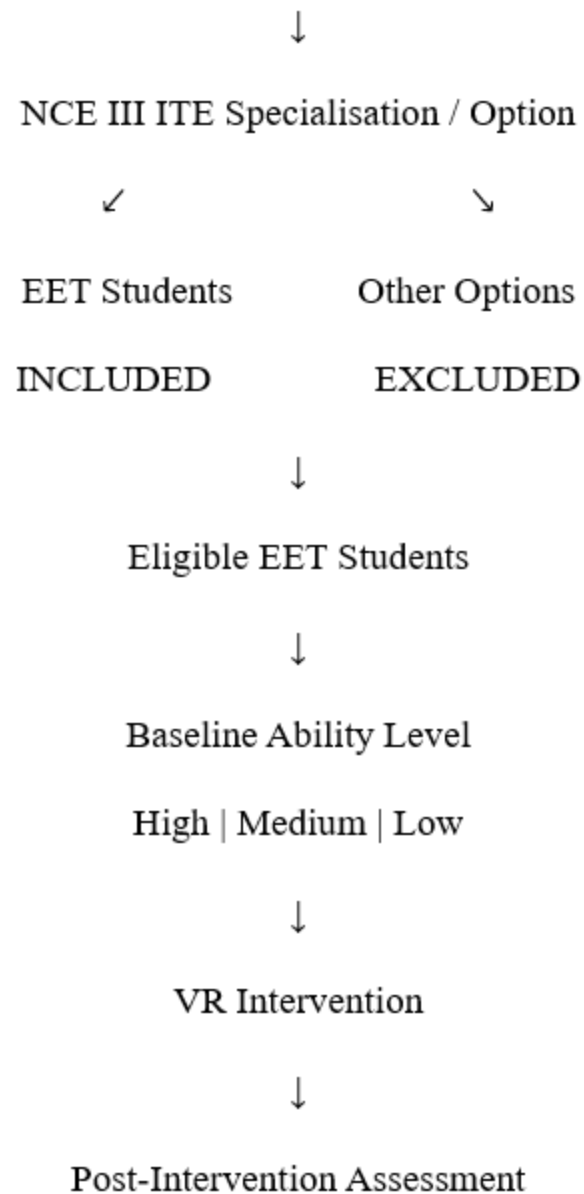


Figure 1

Figure 2.1:Participant Eligibility Criteria



Figure 2

Figure 4.1. Before exposure to VR-based learning, students were distributed according to their ability levels.

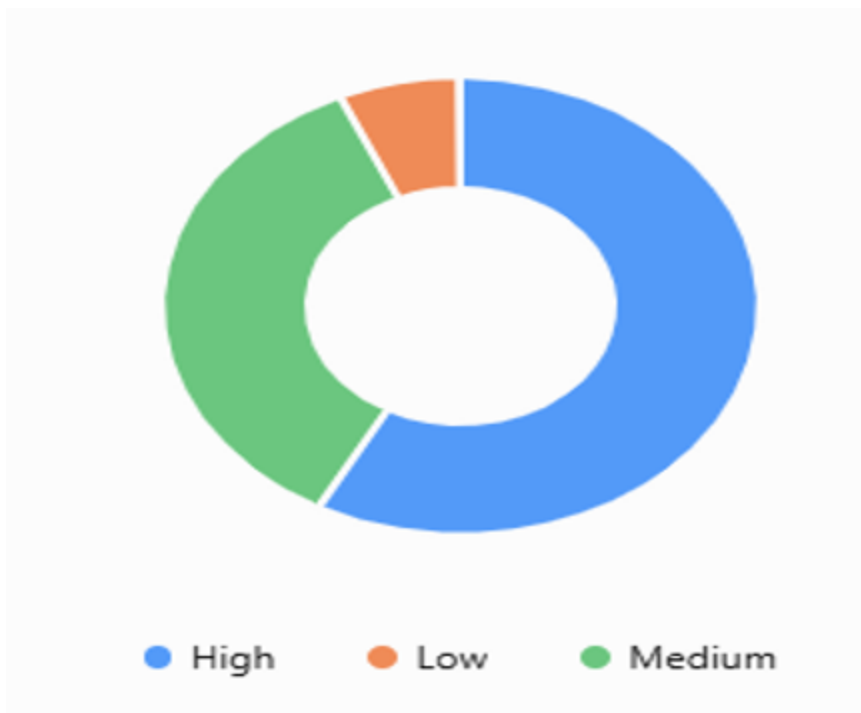


Figure 3

Figure 4.2. After exposure to VR-based learning, students are distributed according to their ability level.

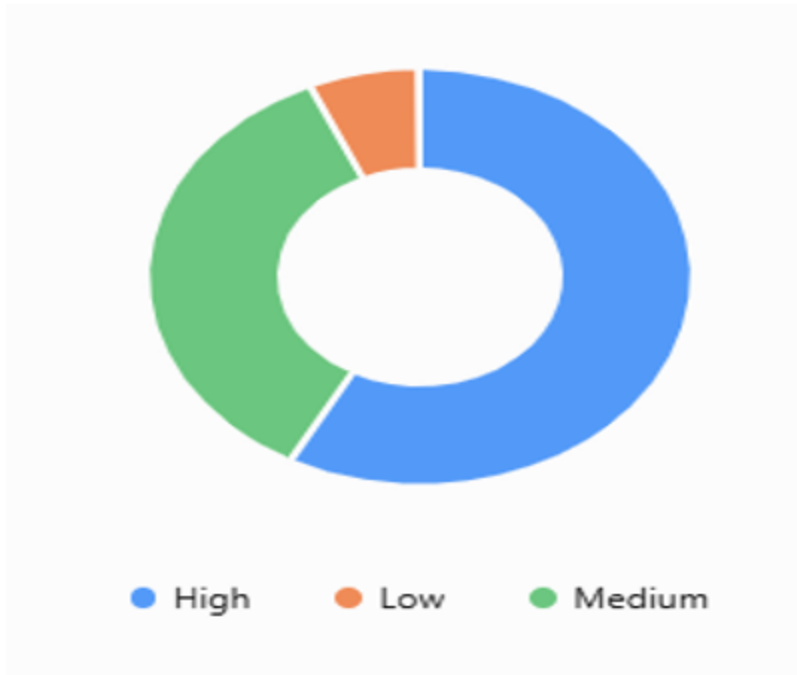


Figure 4

Figure 4.3. The distribution of students' ability levels before and after exposure to VR-based learning.