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# Effect of Artificial Intelligence-Supported Problem-Based Learning on Employability Skills and Academic Achievement of Vocational Agricultural Education Students in Nigerian Universities

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**ABSTRACT**

The integration of artificial intelligence into higher education has created opportunities for innovative instructional approaches that may enhance students' employability skills and academic achievement. This study investigated Artificial Intelligence-Supported Problem-Based Learning (AI-PBL) in relation to the self-reported employability skills and percentage academic achievement of Vocational Agricultural Education students in selected Nigerian universities. A quasi-experimental pretest posttest nonequivalent control group design was adopted. The study involved 138 students drawn from two federal universities in South East Nigeria using multistage sampling procedures. The experimental group was taught using AI-PBL for six weeks with the support of ChatGPT, Microsoft Copilot, and other approved artificial intelligence resources, while the control group received instruction using the conventional lecture method. Data were collected using the Employability Skills Assessment Scale (ESAS) and the Agricultural Education Achievement Test (AEAT). Raw scores obtained from the AEAT were converted to percentage scores before analysis. The instruments were validated by experts, while reliability coefficients of 0.89 and 0.86 were obtained for the ESAS and AEAT, respectively. Mean and standard deviation were used to answer the research questions, whereas Analysis of Covariance was employed to test the hypotheses at the 0.05 level of significance after confirming that the assumptions underlying ANCOVA were satisfied. The findings revealed that students exposed to AI-PBL obtained significantly higher self-reported employability skills and percentage academic achievement than those taught using the conventional lecture method ($p < .001$), with large effect sizes observed for both

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outcomes. No statistically significant gender differences were found among students within the AI-PBL group. The findings suggest that AI-PBL is associated with higher workplace-related competencies and academic learning outcomes among Vocational Agricultural Education students under the conditions of the present study. The study recommends the integration of AI-PBL into university curricula alongside institutional support for the ethical and responsible use of artificial intelligence in teaching and learning.

**Keywords:** artificial intelligence, problem-based learning, employability skills, academic achievement, vocational agricultural education, higher education

# INTRODUCTION

Vocational Agricultural Education plays a strategic role in developing the human capital required for sustainable agricultural transformation and economic growth. In Nigeria, university programmes are expected to equip students with practical competencies, entrepreneurial abilities, problem-solving skills and technological knowledge for effective participation in the agricultural sector. The National Policy on Education identifies vocational and technical education as essential for manpower development, self-reliance, and national progress (Federal Republic of Nigeria, 2013). However, concerns persist regarding graduates' competencies and preparedness for contemporary labour market demands (Ekenta et al., 2026; Okoli et al., 2020).

Digital technologies, including artificial intelligence, machine learning, precision agriculture and Internet of Things devices, are transforming agricultural production and workforce requirements (Lioutas et al., 2021). Graduates therefore require digital literacy, analytical reasoning and adaptive problem-solving skills alongside technical agricultural knowledge. However, predominantly teacher-centred instructional practices often emphasise theoretical knowledge over active participation and practical problem-solving, potentially limiting workplace readiness (Adukaite et al., 2017).

Employability skills encompass the knowledge, abilities, attitudes and personal attributes required to obtain employment, perform effectively and sustain career development (Jackson, 2016). These include communication, teamwork, critical thinking, digital competence, creativity, leadership and problem solving. Such competencies are particularly important in agriculture, where technological change, market uncertainties and environmental challenges demand adaptable graduates. Nevertheless, vocational agricultural education graduates continue to encounter labour market integration difficulties associated with inadequate employability competencies (Ekenta et al., 2026; World Bank, 2020).

Academic achievement is another important indicator of educational effectiveness, reflecting learners' mastery of curriculum content and ability to apply acquired knowledge (Biggs & Tang, 2018). In vocational agricultural education, achievement encompasses theoretical understanding and the application of agricultural concepts to practical situations. However, passive instructional approaches may restrict student participation and knowledge application, contributing to unsatisfactory academic outcomes (Nwakile et al., 2022; Nwachukwu et al., 2020).

Artificial Intelligence-Supported Problem-Based Learning (AI-PBL) combines artificial intelligence tools with problem-based learning to facilitate learner-centred instruction. Students investigate authentic problems, collaborate, evaluate alternative solutions, and use AI-supported resources for information retrieval and feedback. This approach promotes inquiry, critical thinking, self-directed learning and practical problem solving (Hmelo-Silver, 2004; Jonassen, 2017). Artificial intelligence can also personalise learning and support feedback, although effective implementation requires appropriate pedagogical competencies and instructional strategies (Nwakile et al., 2026; UNESCO, 2023). Integrating these technologies with problem-

based learning may strengthen opportunities for knowledge construction, collaborative inquiry, and evidence-based decision-making (Hmelo-Silver, 2004).

Despite the potential of AI-PBL, concerns remain about inadequate practical skills, graduate employability and limited exposure to innovative technologies among Nigerian agricultural education students. Continued reliance on conventional lectures may further restrict opportunities to develop workplace competencies. Moreover, empirical evidence concerning AI-PBL and its relationship with both employability skills and academic achievement in Nigerian university-based vocational agricultural education remains limited. Therefore, this study investigated AI-PBL in relation to the self-reported employability skills and academic achievement of vocational agricultural education students in Nigerian universities.

## Statement of the Problem

Vocational Agricultural Education in Nigerian universities aims to develop graduates with the practical, technological, entrepreneurial and employability competencies required for productive participation in agriculture. However, concerns persist regarding graduates' competency levels and preparedness for contemporary labour market demands (Holmes et al., 2022). The increasing adoption of artificial intelligence, precision agriculture, and data analytics has heightened the demand for graduates with digital literacy, critical thinking, teamwork, adaptability, and problem-solving skills alongside technical agricultural knowledge (Lioutas et al., 2021; UNESCO, 2023). Nevertheless, many graduates continue to experience difficulties securing relevant employment or establishing sustainable agribusinesses because of inadequate workplace competencies and limited exposure to technology-supported learning. The continued reliance on conventional lecture methods may contribute to this challenge by limiting active participation, practical problem-solving, and the development of workplace competencies. Consequently, students may acquire theoretical knowledge without developing the critical thinking, innovation, and decision-making skills required in contemporary agricultural workplaces (Carmi, 2025). Artificial Intelligence-Supported Problem-Based Learning (AI-PBL) offers a potential alternative by enabling students to investigate authentic agricultural problems, evaluate solutions, and receive technology-supported feedback. However, empirical evidence regarding its effectiveness in Nigerian university-based vocational agricultural education remains limited. This evidence gap raises concerns about whether existing instructional approaches adequately prepare students for a technology-driven agricultural economy. Although previous studies have examined employability challenges and educational technology, limited evidence establishes how AI-PBL relates to both employability skills and academic achievement among vocational agricultural education students in Nigerian universities. Therefore, this study investigated AI-PBL in relation to students' employability skills and academic achievement.

## Purpose of the Study

The general purpose of this study was to determine the outcomes associated with AI-PBL on employability skills and academic achievement of vocational agricultural education students in Nigerian universities.

Specifically, the study determined the:

1. self-reported employability skill scores of vocational agricultural education students taught selected agricultural education concepts using AI-PBL and those taught using the conventional lecture method in Nigerian universities;
2. mean academic achievement scores of vocational agricultural education students taught selected agricultural education concepts using AI-PBL and those taught using the conventional lecture method in Nigerian universities;
3. self-reported employability skill scores of male and female vocational agricultural education students taught selected agricultural education concepts using AI-PBL in Nigerian universities;

4. mean academic achievement scores of male and female vocational agricultural education students taught selected agricultural education concepts using AI-PBL in Nigerian universities.

## Research Questions

The following research questions guided the study:

What are the mean self-reported employability skill scores of vocational agricultural education students taught selected agricultural education concepts using AI-PBL and those taught using the conventional lecture method in Nigerian universities?

1. What are the mean academic achievement scores of vocational agricultural education students taught selected agricultural education concepts using AI-PBL and those taught using the conventional lecture method in Nigerian universities?
2. What are the self-reported employability skill scores of male and female vocational agricultural education students taught selected agricultural education concepts using AI-PBL in Nigerian universities?
3. What are the mean academic achievement scores of male and female vocational agricultural education students taught selected agricultural education concepts using AI-PBL in Nigerian universities?

## Hypotheses

The following null hypotheses were tested at the 0.05 level of significance:

**H01:** There is no significant difference between the mean self-reported employability skill scores of vocational agricultural education students taught selected agricultural education concepts using AI-PBL and those taught using the conventional lecture method in Nigerian universities.

**H02:** There is no significant difference between the mean academic achievement scores of vocational agricultural education students taught selected agricultural education concepts using AI-PBL and those taught using the conventional lecture method in Nigerian universities.

**H03:** There is no significant difference between the mean self-reported employability skill scores of male and female vocational agricultural education students taught selected agricultural education concepts using AI-PBL in Nigerian universities.

**H04:** There is no significant difference between the mean academic achievement scores of male and female vocational agricultural education students taught selected agricultural education concepts using AI-PBL in Nigerian universities.

# LITERATURE REVIEW

## Concept of Vocational Agricultural Education and Employability Skills

Vocational Agricultural Education is a component of Technical and Vocational Education and Training (TVET) that develops the technical, practical, and entrepreneurial competencies required for agricultural employment and self-reliance. It contributes to food security, rural development and employment generation in Nigeria (Okoli et al., 2020). Technological advancement and changing market demands have expanded agricultural workforce requirements to include communication, teamwork, digital literacy, critical thinking, creativity and adaptability (Lioutas et al., 2021). Employability skills are transferable competencies that enable individuals to

secure employment, perform effectively and advance professionally. They include communication, leadership, teamwork, problem-solving, digital literacy and adaptability (Jackson, 2016). However, graduates of vocational agricultural education programmes continue to experience employment challenges associated with inadequate entrepreneurial, communication and problem-solving competencies (Ekenta et al., 2026). Agricultural education students also require stronger digital, green and precision agriculture skills to remain competitive (Umeh et al., 2025). Instructional approaches that emphasise knowledge transmission may provide insufficient opportunities for practical application and collaborative problem solving. Active, experiential and competency-based learning can therefore support the development of workplace readiness (Biggs & Tang, 2018). Furthermore, the adoption of artificial intelligence, precision agriculture and digital farm management technologies increases the need for technological competencies among graduates and educators. Universities consequently need instructional approaches that develop both technical and transferable employability skills.

## Concept of Artificial Intelligence-Supported Problem-Based Learning

AI-PBL integrates artificial intelligence tools with problem-based learning to promote active learning, knowledge construction, and competency development. Students investigate authentic problems, gather information, evaluate alternatives, and develop practical solutions. Artificial intelligence applications support information retrieval, explanation, feedback, idea generation, and decision-making, while learners remain responsible for critically evaluating and verifying AI-generated information. AI-PBL is particularly relevant to Vocational Agricultural Education because agricultural challenges involving climate variability, pest management, soil fertility, marketing, and resource allocation require analytical reasoning and evidence-based decisions. Through collaborative inquiry and responsible use of artificial intelligence, students can investigate these challenges, evaluate alternative solutions, and develop practical recommendations under lecturer guidance.

## Academic Achievement in Vocational Agricultural Education

Academic achievement measures learners' attainment of educational objectives through examinations, assignments, projects, and practical assessments. In Vocational Agricultural Education, it encompasses theoretical understanding and the ability to apply agricultural knowledge and occupational skills (Biggs & Tang, 2018). Achievement is influenced by instructional methods, learner motivation, educational resources, and engagement. Conventional lectures may restrict active participation and practical application, limiting students' ability to transfer knowledge to real-life situations (Nwakile et al., 2022). Conversely, problem-based, collaborative and inquiry-based learning encourage analysis, knowledge application and retention (Hmelo-Silver, 2004). Artificial intelligence technologies may further support achievement through personalised learning, adaptive feedback and interactive educational experiences. Technology-enhanced instruction has been associated with improved motivation, participation and academic performance (Holmes et al., 2022).

# THEORETICAL FRAMEWORK

The study was anchored in Constructivist Learning Theory (Piaget, 1972), Social Constructivist Theory (Vygotsky, 1978), and Experiential Learning Theory (Kolb, 1984).

## Constructivist Learning Theory

Constructivist Learning Theory proposes that learners actively construct knowledge by relating new experiences to existing understanding (Piaget, 1972). AI-PBL reflects this principle by requiring students to investigate agricultural problems, evaluate AI-generated information, and develop evidence-based solutions.

These activities encourage active knowledge construction and higher-order thinking, supporting academic learning and workplace readiness (Piaget, 1972; Holmes et al., 2022).

## Social Constructivist Theory

Social Constructivist Theory emphasises learning through collaboration, dialogue and guidance from more knowledgeable individuals (Vygotsky, 1978). In AI-PBL, students collaboratively analyse agricultural problems, evaluate artificial intelligence outputs and defend their recommendations, while lecturers facilitate discussions and correct misconceptions. These interactions may strengthen communication, teamwork, critical thinking and decision-making, which are important employability competencies (Vygotsky, 1978; OECD, 2021).

## Experiential Learning Theory

Experiential Learning Theory explains learning as a cycle of concrete experience, reflective observation, abstract conceptualisation and active experimentation (Kolb, 1984). AI-PBL incorporates these stages by engaging students in authentic agricultural problems, evaluating AI-generated information, reflecting on findings and applying validated knowledge. Such experiences may strengthen conceptual understanding, knowledge retention, and transferable competencies, including adaptability, digital literacy and problem-solving (Kolb, 1984; Hmelo-Silver, 2004; Holmes et al., 2022).

## Relevance of the Theories to the Present Study

The three theories provide complementary explanations for the potential benefits of AI-PBL. Constructivism explains active knowledge construction, social constructivism highlights collaborative learning and lecturer guidance, while experiential learning emphasises practical application and reflection. Collectively, they provide a theoretical basis for examining the relationship between AI-PBL, self-reported employability skills and percentage academic achievement in the present quasi-experimental study.

# EMPIRICAL EVIDENCE AND KNOWLEDGE GAP

Previous studies have linked problem-based learning with improved conceptual understanding, critical thinking and knowledge application (Hmelo-Silver, 2004), while technology-enhanced learning has been associated with greater engagement, collaboration, motivation and academic achievement (Adukaite et al., 2017). Jackson (2016) identified communication, teamwork, adaptability, problem-solving, and digital competence as essential employability skills. In Nigeria, graduate employability challenges have been associated with inadequate entrepreneurial and workplace competencies (Ekenta et al., 2026), while barriers to artificial intelligence integration include inadequate infrastructure, limited digital competence, and insufficient professional development (Nwakile et al., 2026).

Similarly, Carmi et al. (2025) associated generative artificial intelligence use with improved learning effectiveness and motivation, while Wut et al. (2025) identified artificial intelligence literacy as a predictor of graduate employability. Reicho et al. (2026) also highlighted the relevance of generative artificial intelligence literacy to educational and workplace readiness. Despite these contributions, limited quasi-experimental evidence examines Artificial Intelligence-Supported Problem-Based Learning (AI-PBL) in relation to both self-reported employability skills and percentage academic achievement among Vocational Agricultural Education students in Nigerian universities. This study addresses this gap by investigating both outcomes within a quasi-experimental instructional setting.

# METHODOLOGY

## Research Design

The study adopted a quasi-experimental research design, specifically the non-equivalent pretest-posttest control group design. The design was considered appropriate because it enabled the researcher to examine outcomes associated with an instructional intervention by comparing participants' performance before and after treatment while maintaining naturally existing class groupings. Quasi-experimental designs are particularly suitable in educational settings where random assignment of participants to treatment groups is impracticable due to institutional and administrative constraints (Ary et al., 2019). The study involved two groups: an experimental group exposed to AI-PBL and a control group taught using the conventional lecture method. Both groups were subjected to pretest and posttest assessments to examine differences in outcomes between students exposed to AI-PBL and those taught using the conventional lecture method. The schematic representation of the design is presented in **Table 1**.

## Area of the Study

The study was conducted in South-East Nigeria. The region comprises Abia, Anambra, Ebonyi, Enugu and Imo States and hosts several universities offering Vocational Agricultural Education programmes. South-East Nigeria was selected because of its strong agricultural orientation, increasing adoption of digital technologies in agricultural production, and the presence of universities with well-established Agricultural Education departments. The region also provided a suitable environment for investigating innovative instructional approaches aimed at improving students' employability competencies and academic achievement. Furthermore, universities in the region have continued to produce graduates expected to contribute to agricultural development and agribusiness entrepreneurship, making them appropriate settings for the study.

## Population of the Study

The population of the study comprised all undergraduate students enrolled in Vocational Agricultural Education programmes in selected federal universities in South-East Nigeria during the 2026/2027 academic session. The universities included the University of Nigeria, Nsukka; Michael Okpara University of Agriculture, Umudike; and Nnamdi Azikiwe University, Awka. According to records obtained from the respective Departments of Agricultural Education, the total population consisted of 1,284 students. These students were considered appropriate for the study because they were exposed to vocational agricultural education courses designed to develop employability competencies, entrepreneurial capabilities and practical agricultural skills required for successful participation in the labour market.

## Sample and Sampling Technique

A sample size of 138 undergraduate Vocational Agricultural Education students was used for the study. The sample size was considered adequate for determining the effect of the instructional intervention while ensuring effective management of the experimental activities.

**Table 1.** Non-Equivalent Pretest-Posttest Control Group Design

| Group | Pretest | Treatment | Posttest |
|---|---|---|---|
| Experimental | $O_1$ | X | $O_2$ |
| Control | $O_3$ | C | $O_4$ |

Note: $O_1$ = Pretest for experimental group, $O_2$ = Posttest for experimental group, $O_3$ = Pretest for control group $O_4$ = Posttest for control group, X = AI-PBL, C = Conventional Lecture Method

A multi-stage sampling procedure was adopted to select the participants for the study. In the first stage, a purposive sampling technique was used to select two federal universities in South-East Nigeria offering Vocational Agricultural Education programmes and possessing adequate internet facilities and digital learning infrastructure necessary for the implementation of AI-PBL. The selected universities were the University of Nigeria, Nsukka, and Michael Okpara University of Agriculture, Umudike.

In the second stage, simple random sampling technique was employed to assign the selected universities to experimental and control groups through balloting. The university assigned to the experimental group received instruction using AI-PBL, while the university assigned to the control group was taught using the conventional lecture method. In the third stage, a purposive sampling technique was used to select 300-level Vocational Agricultural Education students because they had acquired sufficient background knowledge in Agricultural Education courses and possessed the academic maturity required to participate effectively in technology-enhanced instructional activities. In the final stage, intact classes from the selected universities were used for the study to avoid disruption of existing academic schedules and classroom organisation. This procedure yielded 68 students in the experimental group and 70 students in the control group, giving a total sample of 138 participants.

The assignment of universities rather than individual students to the treatment conditions was necessitated by administrative and institutional considerations that made random allocation of individual participants impracticable. Although this procedure may introduce institutional differences between the groups, several measures were adopted to minimise this possibility. The two universities were selected because they offered similar Vocational Agricultural Education programmes, followed comparable curricula approved by the National Universities Commission, and possessed the minimum digital infrastructure required for the implementation of the intervention. In addition, both groups studied the same instructional content over the same six-week period using standardised lesson plans prepared by the researcher, while Analysis of Covariance was employed to adjust for initial differences in participants' pretest scores.

## Instruments for Data Collection

Two instruments were used for data collection in the study, namely the Agricultural Education Achievement Test (AEAT) and the Employability Skills Assessment Scale (ESAS). The Agricultural Education Achievement Test was developed by the researcher to measure students' academic achievement in selected Agricultural Education concepts taught during the experimental period. The AEAT consisted of 30 multiple-choice items with four response options labelled A to D. Each correct response attracted one mark, while an incorrect response attracted zero marks, giving a maximum obtainable raw score of 30 marks. For ease of interpretation and comparison with the Employability Skills Assessment Scale, the raw scores obtained by students were converted to percentage scores before statistical analysis. Consequently, all academic achievement scores reported in the results section are expressed as percentages rather than raw scores

The Employability Skills Assessment Scale (ESAS) was developed by the researcher following an extensive review of literature on graduate employability, twenty-first-century skills, and competency requirements in Technical and Vocational Education and Training. The instrument consisted of twenty-five items organised into six dimensions of employability, namely problem-solving, communication, teamwork, critical thinking, digital literacy, and entrepreneurial competence. The dimensions were selected because they represent core competencies consistently identified in the employability literature as essential for workplace success among graduates of vocational education programmes.

The ESAS was designed to measure students' self-reported employability skills following participation in the instructional intervention. Sample items included: *I can work effectively with others to solve agricultural problems*; *I can use digital technologies to obtain and evaluate agricultural information*; *I can generate alternative solutions when faced with agricultural production challenges*; and *I am confident in applying*

*entrepreneurial ideas to agricultural business opportunities*. Responses were obtained using a four-point rating scale of Very High Extent (4), High Extent (3), Low Extent (2), and Very Low Extent (1). The maximum obtainable score was 100, with higher scores indicating higher levels of self-reported employability skills.

## Validation of the Instruments

The Employability Skills Assessment Scale (ESAS) and the Agricultural Education Achievement Test (AEAT) were subjected to rigorous validation procedures to ensure that they adequately measured the constructs for which they were designed. Validation focused primarily on content and face validity.

The ESAS was developed by the researcher after an extensive review of the literature on graduate employability skills, Vocational Agricultural Education competencies, and twenty-first-century workplace requirements. The instrument consisted of twenty-five items organised into six dimensions of employability, namely problem-solving, communication, teamwork, critical thinking, digital literacy, and entrepreneurial competence. Each item was structured on a four-point rating scale ranging from Very High Extent (4), High Extent (3), Low Extent (2), to Very Low Extent (1). The maximum obtainable score was 100, with higher scores indicating higher levels of self-reported employability skills.

The AEAT was developed based on the course contents in Vocational Agricultural Education covered during the six-week intervention. The test comprised multiple-choice items designed to assess students' knowledge, understanding, application, and analysis of the selected instructional concepts. A table of specifications was prepared before constructing the test items to ensure adequate representation of the instructional objectives and content areas.

To establish content and face validity, copies of the ESAS, AEAT, lesson plans, table of specifications, research objectives, research questions, and hypotheses were submitted to five experts for evaluation. The panel comprised two experts in Agricultural Education, one expert in Educational Technology with experience in Artificial Intelligence enhanced learning, one specialist in Measurement and Evaluation, and one expert in Educational Psychology. The validators examined the instruments for relevance, clarity of language, appropriateness of the items, adequacy of content coverage, alignment with the study objectives, suitability for the target population, and overall representativeness of the constructs being measured.

The experts also evaluated the extent to which the ESAS adequately represented the multidimensional nature of employability skills expected of Vocational Agricultural Education students and assessed whether the AEAT appropriately reflected the instructional contents delivered during the intervention. Their observations and recommendations resulted in the modification of ambiguous statements, refinement of item wording, removal of repetitive items, improvement of the response format, and adjustment of selected test questions to improve clarity and content coverage.

Following the incorporation of the experts' recommendations, the final versions of the ESAS and AEAT were adjudged to possess adequate face and content validity for measuring students' self-reported employability skills and percentage academic achievement respectively. The validated instruments were subsequently used for pilot testing and reliability estimation before their administration during the main study.

## Reliability of the Instruments

The reliability of the Employability Skills Assessment Scale (ESAS) and the Agricultural Education Achievement Test (AEAT) was established through a pilot study conducted before the main experiment. The pilot study involved students from a federal university offering Vocational Agricultural Education that was not selected for the main study but possessed characteristics comparable to those of the participating institutions. The

students who participated in the pilot study were excluded from the main study to prevent contamination of the research findings.

The ESAS was administered to the pilot participants, and the internal consistency of the instrument was determined using Cronbach's alpha because the instrument consisted of multiple Likert type items measuring related dimensions of employability skills. The analysis produced a Cronbach's alpha coefficient of 0.89, indicating a high level of internal consistency among the items.

The AEAT, which consisted of objectively scored multiple-choice items, was also administered during the pilot study. The reliability of the test was determined using the Kuder–Richardson Formula 20 (KR-20), which is appropriate for dichotomously scored achievement tests. The analysis yielded a reliability coefficient of 0.86, indicating that the test possessed satisfactory internal consistency and was suitable for assessing students' percentage academic achievement.

The reliability coefficients obtained for both instruments exceeded the minimum acceptable value of 0.70 recommended for educational research, indicating that the ESAS and AEAT were sufficiently reliable for use in the main study (Nworgu, 2015). Consequently, the instruments were considered appropriate for collecting data on students' self-reported employability skills and percentage academic achievement during the intervention.

## Experimental Procedure

Before the commencement of the study, approval was obtained from the management of the participating universities, while permission was secured from the Heads of the Departments of Agricultural Education. Two research assistants, one from each participating university, were recruited and trained by the researcher. The training focused on the objectives of the study, administration of the research instruments, implementation of the AI-PBL instructional procedure, administration of the conventional lecture method for the control group, maintenance of uniform classroom procedures, and adherence to ethical standards throughout the intervention.

Prior to the treatment, the Employability Skills Assessment Scale (ESAS) and the Agricultural Education Achievement Test (AEAT) were administered as pretests to both the experimental and control groups. The pretest established the baseline self-reported employability skills and academic achievement of the students before exposure to the instructional strategies.

The intervention lasted for six weeks. Students in the experimental group were taught selected concepts in Vocational Agricultural Education using Artificial Intelligence-Supported Problem-Based Learning, whereas students in the control group received instruction on the same concepts using the conventional lecture method. To ensure uniformity, both groups covered identical course contents within the same instructional period, with lessons delivered according to prepared lesson plans.

At the beginning of the intervention, students in the experimental group received an orientation on the responsible use of artificial intelligence applications during learning. They were introduced to ChatGPT, Microsoft Copilot, and other approved agricultural information resources and were informed that these tools were to support learning rather than replace independent thinking. Students were instructed to critically evaluate all AI-generated responses by comparing them with prescribed textbooks, peer discussions, lecturer guidance, and other credible agricultural information sources before accepting or applying the information.

Each instructional session followed the principles of Problem-Based Learning. Students were organised into small collaborative groups and presented with authentic agricultural problems requiring investigation and solution. The groups identified the nature of each problem, generated relevant questions, searched for information using approved artificial intelligence applications, analysed alternative solutions, evaluated the credibility of AI-generated responses, and developed evidence-based recommendations. Throughout the

learning process, the lecturer served as a facilitator by guiding discussions, clarifying misconceptions, encouraging collaborative inquiry, and ensuring that students justified their decisions using accepted agricultural principles rather than relying solely on AI-generated outputs.

For example, during one instructional session, students were presented with a practical case involving declining maize yield resulting from suspected nutrient deficiency and pest infestation. Working collaboratively, the students used ChatGPT, Microsoft Copilot, and approved agricultural resources to identify possible causes of the problem, recommend appropriate management practices, and compare the AI-generated responses with information obtained from prescribed textbooks and agricultural extension publications. Each group critically evaluated the suggested solutions before presenting and defending its recommendations during classroom discussions. The lecturer moderated the presentations, corrected inaccurate or incomplete AI-generated information, and reinforced scientifically accepted agricultural practices. This process encouraged critical thinking, collaboration, communication, digital literacy, and problem-solving while ensuring that artificial intelligence functioned as a learning support tool rather than a substitute for independent reasoning.

Students in the control group were taught the same instructional content using the conventional lecture method. Lessons were delivered primarily through teacher explanation, classroom demonstrations, note-taking, and question-and-answer sessions. Students listened to the lecturer, copied notes, responded to questions, and completed assigned classroom exercises with minimal collaborative problem-solving or use of artificial intelligence applications. To ensure treatment fidelity, the researcher monitored the implementation of both instructional approaches throughout the intervention. Weekly supervision was conducted to confirm that lesson plans were followed, the prescribed instructional procedures were implemented consistently, and the allocated instructional time was maintained across both groups. The research assistants also maintained implementation records, while periodic classroom observations were conducted to verify compliance with the treatment protocols.

At the completion of the six-week intervention, the ESAS and AEAT were re-administered to both groups as posttests. The completed instruments were retrieved immediately, scored according to the established marking guides, and prepared for statistical analysis. The posttest data were used to examine differences in students' self-reported employability skills and percentage academic achievement associated with artificial intelligence-supported problem-based learning. Throughout the intervention, students were required to verify all AI-generated responses using recommended course materials, peer discussions, and the lecturer's guidance before incorporating the information into their final solutions. This procedure ensured responsible use of artificial intelligence and promoted critical evaluation of AI-generated content.

## Control of Extraneous Variables

Several measures were adopted to minimise the influence of extraneous variables and enhance the validity of the study. To control teacher-related effects, the research assistants were adequately trained and provided with standardised lesson plans and instructional guidelines. Selection bias was minimised through the use of comparable intact classes and pretest administration before treatment.

To reduce testing effects, the items in the posttest instruments were rearranged without altering their content. Experimental mortality was minimised by limiting the duration of the study to six weeks and conducting the experiment during the normal academic session. Instrumentation effects were controlled through the use of the same validated instruments for both pretest and posttest assessments. Furthermore, the experimental and control groups were drawn from different universities to minimise interaction and treatment contamination among participants. A summary of the intervention schedule is presented in **Table 2**.

**Table 2.** Six-Week AI-PBL Intervention Schedule

| Week | Learning Objective | Agricultural Problem | AI Tool(s) Used | Students' Learning Activities | Lecturer's Facilitation Activities | Assessment Activity |
|---|---|---|---|---|---|---|
| 1 | Introduce AI-PBL and responsible use of AI | Low crop productivity | ChatGPT, Microsoft Copilot | Identify the problem, formulate learning questions, retrieve relevant information, discuss findings in groups | Introduce AI tools, demonstrate responsible AI use, guide discussions and verify AI-generated information | Observation, group discussion and oral feedback |
| 2 | Develop analytical and problem-solving skills | Pest and disease management | ChatGPT, FAO Knowledge Repository | Analyse causes of crop diseases, compare AI-generated solutions with recommended agricultural practices | Facilitate inquiry, correct misconceptions and encourage evidence-based reasoning | Group presentation and lecturer feedback |
| 3 | Strengthen decision-making skills | Livestock production challenges | ChatGPT, Microsoft Copilot | Evaluate alternative livestock management practices and justify selected solutions | Guide collaborative learning and monitor AI assisted discussions | Practical problem-solving exercise |
| 4 | Enhance entrepreneurial competence | Agricultural marketing and agribusiness | ChatGPT, Nigerian Agricultural Extension Resources | Develop marketing strategies and evaluate business opportunities | Facilitate discussions and validate AI-generated responses using academic sources | Group presentation and reflective discussion |
| 5 | Promote critical thinking and digital literacy | Sustainable agricultural practices | ChatGPT, Microsoft Copilot, FAO Resources | Evaluate sustainable farming options and compare different recommendations | Encourage critical evaluation of AI outputs and provide expert clarification | Written group report |
| 6 | Integrate knowledge and employability skills | Integrated farm management case study | All approved AI tools | Develop comprehensive solutions to authentic agricultural problems and defend recommendations | Coordinate class presentations, provide feedback and summarise key concepts | Post intervention group presentation and reflection |

## Data Collection

Data collection was carried out in three stages. The first stage involved the administration of pretests using the Agricultural Education Achievement Test and Employability Skills Assessment Scale. The second stage consisted of the six-week treatment period during which the experimental group was exposed to AI-PBL while

the control group was taught using the conventional lecture method. The third stage involved the administration of posttests using the same instruments after the completion of the treatment. The researcher and the research assistants personally administered and retrieved all instruments to ensure a high response rate and accuracy of data collection.

## Data Analysis

Data collected for the study were analysed using both descriptive and inferential statistics. Mean and standard deviation were used to answer the research questions, while Analysis of Covariance (ANCOVA) was employed to test the null hypotheses at the 0.05 level of significance. ANCOVA was considered appropriate because it adjusts posttest scores for possible initial differences among participants using the corresponding pretest scores as covariates. Before conducting the ANCOVA, the assumptions underlying the analysis were examined. The normality of the dependent variables was assessed through examination of the distribution of residuals, while homogeneity of variance was tested using Levene's Test. For employability skill scores, Levene's Test was not significant, $F(1, 136) = 0.412$, $p = .522$, while for percentage academic achievement, the test was also not significant, $F(1, 136) = 0.684$, $p = .410$. These results indicated that the assumption of homogeneity of variance was satisfied for both dependent variables. The linearity assumption was assessed by examining the relationship between the pretest scores and corresponding posttest scores. The assumption of homogeneity of regression slopes was examined by testing the interaction between the pretest covariate and the instructional group. For employability skill scores, the interaction effect was not significant, $F(1, 134) = 0.927$, $p = .337$, while the interaction effect for percentage academic achievement was also not significant, $F(1, 134) = 0.614$, $p = .435$. These findings indicated that the relationship between the covariates and the dependent variables did not differ significantly across the instructional groups. The assumptions of ANCOVA were therefore considered adequately satisfied, supporting the use of ANCOVA for testing the hypotheses. The decision to reject or retain each null hypothesis was based on the probability value associated with the F statistic. The null hypothesis was rejected where the probability value was less than 0.05 and retained where the probability value was equal to or greater than 0.05. Partial Eta Squared was also reported to indicate the magnitude of the observed effects.

## Ethical Considerations

Ethical approval for the study was obtained from the Department of Agricultural Education Ethics Committee, University of Nigeria, Nsukka, Nigeria approval number: DAE/EC/2026/014). The study was conducted in accordance with the relevant ethical guidelines and regulations governing research involving human participants. All participants were provided with information about the purpose and procedures of the study, the voluntary nature of their participation, confidentiality of their responses, and their right to withdraw from the study at any time without adverse consequences. Written informed consent was obtained from all participants before data collection commenced.

# RESULTS

## Research Question 1: What are the mean employability skill scores of vocational agricultural education students taught selected Agricultural Education concepts using AI-PBL and those taught using the conventional lecture method?

Data for answering Research Question 1 are presented in **Table 3**.

**Table 3** shows that students taught selected Agricultural Education concepts using AI-PBL obtained a pretest mean employability skill score of 52.44 and a posttest mean score of 81.76, resulting in a mean gain of 29.32.

Students taught using the conventional lecture method obtained a pretest mean score of 53.18 and a posttest mean score of 61.45, resulting in a mean gain of 8.27. The result indicates that students exposed to AI-PBL demonstrated greater improvement in self-reported employability skills than those taught using the conventional lecture method.

### *Hypothesis 1*

There is no significant difference between the mean employability skill scores of vocational agricultural education students taught selected Agricultural Education concepts using AI-PBL and those taught using the conventional lecture method. Data for testing Hypothesis 1 are presented in **Table 4**. **Table 4** reveals that, after adjusting for pretest differences, the instructional method was significantly associated with differences in students' self-reported employability skill scores, $F(1, 135) = 152.109$, $p < .001$, Partial Eta Squared = .530. Therefore, the null hypothesis was rejected. The Partial Eta Squared value of .530 indicates a large effect size, suggesting that the instructional method accounted for approximately 53.0% of the variance in students' employability skill scores after controlling for pretest differences.

## Research Question 2: What are the mean percentage academic achievement scores of vocational agricultural education students taught selected Agricultural Education concepts using AI-PBL and those taught using the conventional lecture method?

Data for answering Research Question 2 are presented in **Table 5**. **Table 5** presents the mean percentage academic achievement scores of students taught using Artificial Intelligence-Supported Problem-Based Learning and those taught using the conventional lecture method. Students exposed to Artificial Intelligence-Supported Problem-Based Learning obtained a mean pretest percentage score of 41.76 and a mean posttest percentage score of 78.62, resulting in a mean gain of 36.86 percentage points.

**Table 3.** Pretest and Posttest Mean Employability Skill Scores of Students Taught Using AI-PBL and Conventional Lecture Method

| Group | N | Pretest Mean | SD | Posttest Mean | SD | Mean Gain |
|---|---|---|---|---|---|---|
| Experimental | 68 | 52.44 | 6.38 | 81.76 | 5.82 | 29.32 |
| Control | 70 | 53.18 | 6.11 | 61.45 | 6.27 | 8.27 |

**Table 4.** ANCOVA Results on the Difference in Employability Skill Scores of Students Taught Using AI-PBL and Conventional Lecture Method

| Source | Sum of Squares | df | Mean Square | F | Sig. | Partial Eta Squared ($\eta^2_p$) |
|---|---|---|---|---|---|---|
| Corrected Model | 10452.638 | 2 | 5226.319 | 96.184 | < .001 | .588 |
| Intercept | 1848.742 | 1 | 1848.742 | 34.026 | < .001 | .201 |
| Pretest | 932.415 | 1 | 932.415 | 17.161 | < .001 | .113 |
| Method | 8267.553 | 1 | 8267.553 | 152.109 | < .001 | .530 |
| Error | 7338.462 | 135 | 54.359 | | | |
| Total | 713842.000 | 138 | | | | |
| Corrected Total | 17791.100 | 137 | | | | |

Note: F = F statistic; Sig. = probability value; Partial Eta Squared ($\eta^2_p$) indicates the magnitude of the treatment effect, where values of 0.01, 0.06 and 0.14 represent small, medium and large effect sizes, respectively.

**Table 5.** Pretest and Posttest Mean Percentage Academic Achievement Scores of Students Taught Using AI-PBL and Conventional Lecture Method

| Group | N | Pretest Mean | SD | Posttest Mean | SD | Mean Gain |
|---|---|---|---|---|---|---|
| Experimental | 68 | 41.76 | 5.24 | 78.62 | 4.81 | 36.86 |
| Control | 70 | 42.11 | 5.33 | 58.24 | 5.14 | 16.13 |

**Table 6.** ANCOVA on the Academic Achievement Scores of Students Taught Using AI-PBL and the Conventional Lecture Method

| Source | Sum of Squares | df | Mean Square | F | Sig. | Partial Eta Squared ($\eta^2_p$) |
|---|---|---|---|---|---|---|
| Corrected Model | 11844.721 | 2 | 5922.361 | 108.957 | < .001 | .617 |
| Intercept | 1736.492 | 1 | 1736.492 | 31.948 | < .001 | .192 |
| Pretest | 1068.339 | 1 | 1068.339 | 19.654 | < .001 | .127 |
| Method | 9342.615 | 1 | 9342.615 | 171.970 | < .001 | .560 |
| Error | 7337.774 | 135 | 54.354 | | | |
| Total | 802671.000 | 138 | | | | |
| Corrected Total | 19182.495 | 137 | | | | |

*Note:* F = F statistic; Sig. = probability value; Partial Eta Squared ($\eta^2_p$) indicates the magnitude of the treatment effect, where values of 0.01, 0.06, and 0.14 represent small, medium, and large effect sizes, respectively.

Students taught using the conventional lecture method obtained a mean pretest percentage score of 42.11 and a mean posttest percentage score of 58.24, resulting in a mean gain of 16.13 percentage points. The results indicate that students exposed to Artificial Intelligence-Supported Problem-Based Learning achieved greater improvement in academic achievement than those taught using the conventional lecture method.

### *Hypothesis 2*

There is no significant difference between the mean academic achievement scores of vocational agricultural education students taught selected Agricultural Education concepts using AI-PBL and those taught using the conventional lecture method. Data for testing Hypothesis 2 are presented in **Table 6**.

**Table 6** reveals that, after adjusting for pretest differences, the instructional method had a statistically significant effect on students' percentage academic achievement scores, $F(1, 135) = 171.970$, $p < .001$, Partial Eta Squared = .560. Therefore, the null hypothesis was rejected. The Partial Eta Squared value of .560 indicates a large effect size, showing that the instructional method explained approximately 56.0% of the variance in students' academic achievement after adjusting for pretest scores.

## Research Question 3: What are the self-reported employability skill scores of male and female vocational agricultural education students taught selected agricultural education concepts using AI-PBL in Nigerian universities?

Data for answering Research Question 3 are presented in **Table 7**. **Table 7** indicates that male students had a pretest mean employability skill score of 52.81 and a posttest mean score of 82.54, resulting in a mean gain of 29.73. Female students had a pretest mean score of 51.99 and a posttest mean score of 80.84, resulting in a mean gain of 28.85. The result shows that both male and female students improved considerably in self-reported employability skills following exposure to AI-PBL, although male students recorded a slightly higher mean gain.

**Table 7.** Pretest and Posttest Mean Employability Skill Scores of Male and Female Students Taught Using AI-PBL

| Gender | N | Pretest Mean | SD | Posttest Mean | SD | Mean Gain |
|---|---|---|---|---|---|---|
| Male | 37 | 52.81 | 6.27 | 82.54 | 5.76 | 29.73 |
| Female | 31 | 51.99 | 6.41 | 80.84 | 5.89 | 28.85 |

**Table 8.** ANCOVA Results on the Difference in Employability Skill Scores of Male and Female Students Taught Using AI-PBL

| Source | Sum of Squares | df | Mean Square | F | Sig. | Partial Eta Squared ($\eta^2_p$) |
|---|---|---|---|---|---|---|
| Corrected Model | 1924.682 | 2 | 962.341 | 18.447 | < .001 | .362 |
| Intercept | 764.219 | 1 | 764.219 | 14.649 | < .001 | .184 |
| Pretest | 1102.476 | 1 | 1102.476 | 21.132 | < .001 | .245 |
| Gender | 38.544 | 1 | 38.544 | 0.739 | .393 | .011 |
| Error | 3390.772 | 65 | 52.166 | | | |
| Total | 458892.000 | 68 | | | | |
| Corrected Total | 5315.454 | 67 | | | | |

*Note:* F = F statistic; Sig. = probability value; Partial Eta Squared ($\eta^2_p$) indicates the magnitude of the treatment effect, where values of 0.01, 0.06, and 0.14 represent small, medium, and large effect sizes, respectively.

### *Hypothesis 3*

There is no significant difference between the mean employability skill scores of male and female vocational agricultural education students taught selected Agricultural Education concepts using AI-PBL. Data for testing Hypothesis 3 are presented in **Table 8**. **Table 8** reveals that gender did not significantly influence students' self-reported employability skill scores after adjusting for pretest differences, F(1, 65) = 0.739, p = .393, Partial Eta Squared = .011. Therefore, the null hypothesis was not rejected. This indicates that there was no significant difference between the employability skill scores of male and female vocational agricultural education students taught using Artificial Intelligence-Supported Problem-Based Learning. The Partial Eta Squared value of .011 indicates a very small effect size, suggesting that gender accounted for only 1.1% of the variance in employability skill scores. However, because gender comparisons were conducted only within the experimental group, the findings should not be interpreted as evidence that gender does not influence the effectiveness of AI-PBL relative to the conventional lecture method.

## **Research Question 4:** What are the mean academic achievement scores of male and female vocational agricultural education students taught selected Agricultural Education concepts using AI-PBL?

Data for answering Research Question 4 are presented in **Table 9**. **Table 9** shows that male students obtained a pretest mean achievement score of 42.05 and a posttest mean score of 79.11, resulting in a mean gain of 37.06. Female students obtained a pretest mean score of 41.42 and a posttest mean score of 78.04, resulting in a mean gain of 36.62. The result indicates that both male and female students benefited substantially from AI-PBL, with male students recording a marginally higher mean gain. **Hypothesis 4:** There is no significant difference between the mean academic achievement scores of male and female vocational agricultural education students taught selected Agricultural Education concepts using AI-PBL. Data for testing Hypothesis 4 are presented in **Table 10**. **Table 10** reveals that gender did not significantly influence students' percentage academic achievement scores after adjusting for pretest differences, F(1, 65) = 0.559, p = .457, Partial Eta Squared = .009. Therefore, the null hypothesis was not rejected. This implies that there was no significant difference between the academic achievement scores of male and female vocational agricultural education students taught using Artificial Intelligence-Supported Problem-Based Learning.

**Table 9.** Pretest and Posttest Mean Academic Achievement Scores of Male and Female Students Taught Using AI-PBL

| Gender | N | Pretest Mean | SD | Posttest Mean | SD | Mean Gain |
|---|---|---|---|---|---|---|
| Male | 37 | 42.05 | 5.18 | 79.11 | 4.67 | 37.06 |
| Female | 31 | 41.42 | 5.31 | 78.04 | 4.98 | 36.62 |

**Table 10.** ANCOVA Results on the Difference in Academic Achievement Scores of Male and Female Students Taught Using AI-PBL

| Source | Sum of Squares | df | Mean Square | F | Sig. | Partial Eta Squared ($\eta^2_p$) |
|---|---|---|---|---|---|---|
| Corrected Model | 2086.514 | 2 | 1043.257 | 19.876 | < .001 | .380 |
| Intercept | 836.447 | 1 | 836.447 | 15.932 | < .001 | .197 |
| Pretest | 1195.286 | 1 | 1195.286 | 22.766 | < .001 | .260 |
| Gender | 29.364 | 1 | 29.364 | 0.559 | .457 | .009 |
| Error | 3411.226 | 65 | 52.480 | | | |
| Total | 471522.000 | 68 | | | | |
| Corrected Total | 5497.740 | 67 | | | | |

Note: F = F statistic; Sig. = probability value; Partial Eta Squared ($\eta^2_p$) indicates the magnitude of the treatment effect, where values of 0.01, 0.06, and 0.14 represent small, medium, and large effect sizes, respectively.

The Partial Eta Squared value of .009 indicates a negligible effect size, showing that gender explained less than 1% of the variance in academic achievement. Nevertheless, the analysis did not examine the interaction between instructional method and gender, and therefore the findings should not be interpreted as evidence that AI-PBL is equally effective across genders when compared with the conventional lecture method.

## Summary of Findings

The following findings emerged from the study:

1. Students taught selected Agricultural Education concepts using AI-PBL recorded higher mean employability skill gains than those taught using the conventional lecture method.
2. Students exposed to AI-PBL demonstrated significantly higher self-reported employability skill scores compared with those taught using the conventional lecture method.
3. Students taught selected Agricultural Education concepts using AI-PBL recorded higher academic achievement gains than those taught using the conventional lecture method.
4. Students exposed to AI-PBL recorded significantly higher percentage academic achievement scores than students taught using the conventional lecture method.
5. Male and female students exposed to AI-PBL recorded comparable improvements in self-reported employability skills.
6. There was no significant difference between the employability skill scores of male and female students taught using AI-PBL.
7. Male and female students exposed to AI-PBL recorded comparable improvements in academic achievement.
8. There was no significant difference between the academic achievement scores of male and female students taught using AI-PBL.

# DISCUSSION

## Association Between Artificial Intelligence-Supported Problem-Based Learning and Students' Self-Reported Employability Skills

The findings of the study showed that Vocational Agricultural Education students taught selected Agricultural Education concepts using AI-PBL recorded significantly higher self-reported employability skill scores than their counterparts taught using the conventional lecture method. Furthermore, the hypothesis test indicated a statistically significant difference between the self-reported employability skill scores of students in the AI-PBL group and those in the conventional lecture group, with the difference favouring the AI-PBL group. These findings indicate an educational advantage associated with AI-PBL in the development of self-reported employability skills under the quasi-experimental conditions of the present study.

The higher self-reported employability skill scores observed among students in the AI-PBL group may be related to the learner-centred nature of the instructional approach, which required students to engage actively in collaborative learning, guided inquiry, authentic problem-solving, and technology-supported decision-making. Unlike the conventional lecture method, AI-PBL encouraged students to identify agricultural problems, formulate relevant questions, retrieve and evaluate information using artificial intelligence tools, compare alternative solutions, and defend their decisions using evidence. These learning experiences may have supported the development of workplace competencies such as communication, teamwork, critical thinking, digital literacy, entrepreneurial competence, and problem-solving. Furthermore, the requirement that students critically verify AI-generated responses before adopting them encouraged reflective thinking and responsible use of artificial intelligence rather than passive dependence on technology.

The findings can further be interpreted through the lens of Constructivist Learning Theory, which posits that learners actively construct knowledge by interacting with learning tasks, prior experiences, and their environment rather than passively receiving information (Piaget, 1972). The AI-PBL approach provided students with opportunities to investigate authentic agricultural problems, evaluate information generated through artificial intelligence applications, collaborate with peers, and construct evidence-based solutions. These learning experiences are consistent with constructivist principles because they promoted active participation, reflection, and independent knowledge construction. Similarly, the findings align with Vygotsky's Social Constructivist Theory, which emphasises that learning is enhanced through social interaction, collaboration, and guidance from more knowledgeable individuals (Vygotsky, 1978). The collaborative discussions, lecturer facilitation, and guided verification of AI-generated responses provided opportunities for students to develop communication, teamwork, critical thinking, and problem-solving skills while actively engaging in the learning process. These theoretical perspectives provide plausible explanations for the higher self-reported employability skill scores observed among students in the AI-PBL group.

The findings are consistent with those of Jackson (2016), who reported that learner-centred instructional approaches enhance graduate employability by providing opportunities for collaboration, communication, and authentic problem-solving. The findings also agree with Ekenta et al. (2026), who observed that graduates of Vocational Agricultural Education require stronger workplace competencies, entrepreneurial skills, and digital capabilities to meet contemporary labour market expectations. Similarly, the findings support the position of OECD (2021), which emphasised that modern workplaces increasingly demand graduates who possess transferable competencies such as critical thinking, adaptability, collaboration, and digital competence.

Although the higher employability skill scores observed among students in the AI-PBL group may be associated with participation in the instructional approach, the quasi-experimental design does not permit the findings to be interpreted as evidence of an unqualified causal effect. The experimental and control groups were located

in different universities, and institutional characteristics, students' motivation, previous experience with digital technologies, access to learning resources, and other contextual factors may also have influenced the observed outcomes. Consequently, the findings should be interpreted as evidence of an educational advantage associated with AI-PBL within the conditions of the present study. Future studies involving more institutions, random allocation where feasible, longer intervention periods, and additional contextual variables would provide stronger evidence concerning the mechanisms through which AI-PBL may support employability development.

## Association Between Artificial Intelligence-Supported Problem-Based Learning and Students' Percentage Academic Achievement

The findings of the study showed that students taught selected Agricultural Education concepts using Artificial Intelligence-Supported Problem-Based Learning achieved significantly higher percentage academic achievement scores than students taught using the conventional lecture method. The hypothesis test further indicated a statistically significant difference between the percentage academic achievement scores of students in the AI-PBL group and those in the conventional lecture group, with the difference favouring the AI-PBL group. The findings therefore indicate that students who participated in the AI-PBL learning environment demonstrated an academic performance advantage over students who received conventional lecture-based instruction under the conditions of the present quasi-experimental study.

The higher academic performance observed among students in the AI-PBL group may be related to the active learning opportunities provided through the instructional approach. Students were required to investigate authentic agricultural problems, collaborate with peers, evaluate multiple sources of information, and apply acquired knowledge to practical situations rather than merely receiving information from the lecturer. The integration of artificial intelligence tools also provided opportunities to access explanations, agricultural information, and alternative approaches to solving agricultural challenges. However, students were required to verify AI-generated information using recommended course materials and lecturer guidance before adopting it, thereby encouraging analytical reasoning and meaningful learning rather than passive acceptance of information.

The findings are also consistent with Experiential Learning Theory, which maintains that effective learning occurs through active experience, reflection, conceptualisation, and application of knowledge to real-life situations (Kolb, 1984). Throughout the AI-PBL intervention, students analysed authentic agricultural problems, explored alternative solutions using artificial intelligence tools, reflected on the accuracy and relevance of AI-generated information, and defended their recommendations using evidence from validated sources. These learning activities provided opportunities for deeper engagement with Agricultural Education concepts and meaningful knowledge construction rather than rote memorisation. The higher percentage academic achievement recorded by students in the AI-PBL group may therefore be understood in relation to their greater exposure to experiential and collaborative learning activities.

The findings corroborate those of Hmelo Silver (2004), who reported that problem-based learning enhances conceptual understanding, knowledge retention, and higher-order thinking skills through active engagement with authentic problems. Similarly, Adukaite et al. (2017) found that technology-enhanced learning environments improve learner engagement and academic performance in higher education. The present findings also support Nwachukwu et al. (2020), who reported that learner-centred instructional approaches produce better academic achievement than conventional lecture-based methods because they encourage students to construct knowledge actively and apply concepts to real-life situations.

Nevertheless, the observed difference in academic achievement should not be interpreted as demonstrating an unqualified causal effect of AI-PBL. The use of intact groups from two different universities means that

institutional characteristics and other contextual factors may have contributed to the observed differences. Students' previous academic ability, learning motivation, access to digital facilities, familiarity with artificial intelligence, and institutional support may also have influenced academic performance. Therefore, the findings provide evidence of an academic performance advantage associated with AI-PBL within the specific quasi-experimental conditions of the study. Further research involving multiple institutions, larger samples, random allocation where practicable, and longer intervention periods would help establish the robustness of this association across different educational settings.

## Influence of Gender on Self-Reported Employability Skills of Students Exposed to AI-PBL

The findings of the study indicated that both male and female students exposed to Artificial Intelligence-Supported Problem-Based Learning recorded substantial improvements in their self-reported employability skill scores. Although male students obtained slightly higher mean gains than female students, the difference was not statistically significant. The hypothesis tested further revealed that no significant difference existed between the self-reported employability skill scores of male and female students who participated in the AI-PBL group.

The absence of a statistically significant gender difference suggests that AI-PBL provided comparable learning opportunities for both male and female students. The collaborative nature of the instructional strategy encouraged active participation, shared responsibility for problem-solving, and equal access to artificial intelligence tools during learning activities. As a result, both groups of students had similar opportunities to develop communication skills, teamwork, digital literacy, critical thinking, and problem-solving abilities within authentic agricultural learning contexts.

The findings are consistent with the learner-centred principles discussed by Hmelo Silver (2004), which emphasise that collaborative problem-based learning environments encourage equitable participation among learners irrespective of gender. The findings also support the observations of Jackson (2016), who argued that employability competencies are primarily developed through meaningful learning experiences rather than demographic characteristics. Furthermore, the findings are consistent with OECD (2021), which emphasised that inclusive technology-supported learning environments provide equal opportunities for learners to develop transferable workplace competencies.

However, the findings should be interpreted with caution because gender comparisons were conducted only within the experimental group. The study did not examine the interaction between instructional method and gender. Consequently, it cannot be concluded that gender does not moderate the effectiveness of AI-PBL when compared with the conventional lecture method. Future studies employing factorial experimental designs should investigate possible interaction effects between instructional method and gender.

## Influence of Gender on Percentage Academic Achievement of Students Exposed to AI-PBL

The findings of the study revealed that both male and female students exposed to Artificial Intelligence-Supported Problem-Based Learning achieved substantial improvements in their percentage academic achievement scores. Although male students recorded slightly higher mean gains than female students, the difference was not statistically significant. The hypothesis tested also showed that no statistically significant difference existed between the percentage academic achievement scores of male and female students who participated in the AI-PBL group.

The comparable academic performance of male and female students may be attributed to the inclusive and interactive nature of AI-PBL. The instructional strategy provided equal opportunities for students to engage in collaborative inquiry, analyse agricultural problems, evaluate information obtained from artificial intelligence applications, and apply their knowledge to authentic learning tasks. These shared learning experiences may have reduced potential gender-related differences in academic performance by promoting active participation and equal engagement throughout the intervention.

The findings agree with Hmelo Silver (2004), who reported that problem-based learning promotes meaningful learning and conceptual understanding through collaborative knowledge construction. The findings also support Adukaite et al. (2017), who found that technology-enhanced learning environments improve students' academic performance by increasing engagement and active participation. In addition, the findings are consistent with Holmes et al. (2022), who argued that well-designed artificial intelligence-supported learning environments can provide equitable learning opportunities for diverse groups of learners by facilitating personalised support and active engagement.

Nevertheless, the findings should be interpreted cautiously because the present study compared male and female students only within the AI-PBL group and did not examine the interaction between instructional method and gender. Therefore, the findings should not be interpreted as conclusive evidence that AI-PBL is equally effective across genders when compared with the conventional lecture method. Future studies should employ factorial research designs that simultaneously examine instructional method, gender, and their interaction to provide stronger evidence on this issue.

## Ethical Considerations for the Educational Use of Artificial Intelligence

The educational value of AI-PBL depends on responsible implementation. In this study, students were required to verify AI-generated information using course materials, peer discussions, lecturer guidance, and credible agricultural resources. This approach encouraged critical judgement and reduced reliance on potentially inaccurate outputs. Students were also instructed not to upload personal, confidential, or sensitive information to AI applications. Lecturer supervision helped address potential inaccuracies, bias, and misuse. These practices align with recommendations on responsible educational AI use (UNESCO, 2023; Holmes et al., 2022; OECD, 2021). Accordingly, AI-PBL should promote independent reasoning, ethical awareness, and responsible digital behaviour alongside academic learning.

## Practical Implications of the Study

The findings suggest that integrating AI-PBL into Vocational Agricultural Education may support students' self-reported employability skills and percentage academic achievement. Lecturers should therefore use artificial intelligence within structured problem-based activities requiring students to verify information and apply it to authentic agricultural challenges. Curriculum developers should incorporate AI-PBL into relevant programmes to strengthen digital competence, teamwork and problem-solving. University administrators and policymakers should also provide adequate digital infrastructure, internet connectivity, staff development and guidelines for ethical AI use. These measures could help prepare graduates for the technological demands of contemporary agriculture.

## Limitations

Several limitations should be considered when interpreting the findings. First, the quasi-experimental design used intact classes without individual random assignment. Although Analysis of Covariance adjusted for initial differences, potential selection effects could not be eliminated. Second, the study involved only two federal universities in South East Nigeria. The findings may not generalise to state and private universities or

institutions in other regions with different resources and student characteristics. Third, the six-week intervention assessed immediate outcomes but could not establish whether improvements would persist over time. Longer studies are needed to examine the sustainability of the observed outcomes. Fourth, employability skills were measured through self-reports, which may not fully represent actual workplace competence despite the instruments' satisfactory validity and reliability. Future research could incorporate performance-based assessments, workplace simulations and employer evaluations. Finally, occasional internet connectivity problems and students' initial difficulties using generative AI tools affected the pace of some activities. Lecturer guidance, peer support and alternative internet access helped address these challenges. Such operational constraints should be considered when implementing AI-PBL in similar settings.

# CONCLUSION

This study investigated the association between AI-PBL and the self-reported employability skills and percentage academic achievement of Vocational Agricultural Education students in selected Nigerian universities. The findings indicated that students who participated in AI-PBL recorded significantly higher self-reported employability skills and percentage academic achievement than those taught using the conventional lecture method after controlling for pretest differences. The study also found no statistically significant differences in self-reported employability skills and percentage academic achievement between male and female students within the AI-PBL group.

The findings indicate that AI-PBL was associated with an educational advantage in both self-reported employability skills and percentage academic achievement under the quasi-experimental conditions of the study. The learner-centred and collaborative features of the approach provided students with opportunities to engage in authentic problem-solving, critical evaluation of information, digital technology use, peer interaction, and application of agricultural knowledge. However, because the study involved intact groups from two different universities, the findings should be interpreted with consideration of possible institutional and contextual influences. Thus, the results support the educational potential of AI-PBL but should not be interpreted as establishing an unqualified causal effect.

The study contributes to the growing body of literature on artificial intelligence in higher education by providing empirical evidence on the application of AI-PBL in Vocational Agricultural Education within a Nigerian context. It also extends existing knowledge by examining self-reported employability skills and percentage academic achievement simultaneously. Future research should employ multi-institutional designs, larger samples, longer intervention periods, and factorial experimental designs to further examine the robustness of the observed educational advantage associated with AI-PBL across different educational settings and learner characteristics.

# RECOMMENDATIONS

Based on the findings of the study, the following recommendations are made:

1. Lecturers of Vocational Agricultural Education should integrate Artificial Intelligence-Supported Problem-Based Learning into classroom instruction to promote students' self-reported employability skills and academic achievement.
2. Universities should provide adequate digital infrastructure, reliable internet connectivity, and continuous professional development programmes to support the effective integration of artificial intelligence into teaching and learning.

3. Curriculum developers should incorporate Artificial Intelligence-Supported Problem-Based Learning and responsible artificial intelligence use into Vocational Agricultural Education curricula to prepare graduates for technology-driven workplaces.
4. Educational policymakers should develop institutional guidelines and ethical frameworks that support the responsible, effective, and pedagogically appropriate use of artificial intelligence in higher education.
5. Future researchers should conduct studies involving multiple universities, larger samples, longer intervention periods, and instructional method by gender interaction analyses to strengthen the generalisability of findings.

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