

Design and Evaluation of an Inclusive AI-Driven Learning System for Personalized Technical Skill Acquisition in Resource-Constrained Environments

Onyenweuwa Basil O.¹, Ogu Philip E², Utu-Baku M. A³., Nwokoma Chukwuma U.⁴

¹Department of Computer Science, Imo State University, Owerri

²Department of Chemistry, Alvan Ikeoku Federal College of Education, Owerri

^{3,4}Department of Computer Science. Federal College of Education Obudu, cross River State

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ABSTRACT

Artificial Intelligence (AI) presents transformative opportunities for educational personalization, yet traditional adaptive learning platforms remain constrained by high bandwidth requirements, complex cloud dependencies, and standardized linear instruction. In resource-constrained technical and vocational education and training (TVET) settings, these dependencies exacerbate inequality. This study presents the design, architectural prototype, and preliminary in-silico evaluation of a lightweight AI-driven learning system tailored for dynamic technical skill acquisition. Following Design Science Research (DSR) methodology, the system utilizes a Random Forest classifier to profile learners into four competency tiers (Beginner, Intermediate, Advanced, and Expert) based on multidimensional engagement and performance indicators. Benchmarking on a synthetic dataset (N = 14,003 learner records) demonstrates that the pre-examination diagnostic model—relying strictly on continuous behavioural engagement metrics (e.g., assignment completion, attendance, study hours) without exam scores—achieves 92.4% classification accuracy (F1-score = 0.924). Incorporating post-hoc summative examination scores yields a 100.0% classification result, confirming deterministic mathematical reconstruction of established grading rules. Feature importance analysis shows low predictive weights for Gender (3.35%), Internet Access (0.78%), and EduTech Access (2.97%), though Age accounts for 11.89% of predictive weight in pre-examination profiling. Quantitative benchmark measurements confirm a lightweight model footprint (< 15MB) and minimal inference latency (< 12ms), supporting potential offline edge deployment. These findings demonstrate the architectural feasibility of early pedagogical intervention in low-bandwidth settings, while highlighting the necessity of live pilot trials for operational validation.

Keywords: Artificial Intelligence in Education (AIED), Personalized Learning, Technical Skill Acquisition, Random Forest Classifier, Resource-Constrained Environments, Inclusive Education, Synthetic Benchmark.

INTRODUCTION

Artificial Intelligence (AI) is increasingly being applied to education to improve learning personalization, assessment, learner support, and instructional decision-making. AI-driven learning systems can analyse learner interactions and performance and use the resulting information to recommend learning resources, adjust learning pathways, provide feedback, and identify areas requiring additional support. Recent systematic reviews have shown that adaptive and personalized learning systems can improve learning outcomes and engagement when appropriately integrated into educational practice (Wang et al., 2024; Bayly-Castaneda et al., 2024). However, the benefits of these technologies are not equally accessible to all learners.

The challenge is more pronounced in resource-constrained educational environments, where learners and institutions may face limited internet connectivity, inadequate digital devices, unreliable electricity, insufficient digital infrastructure, and limited technical support. UNESCO's recent recommendations on digital

technologies for inclusive education emphasize that technology-supported learning must address accessibility, affordability, infrastructure, digital literacy, and the diverse needs of learners rather than merely introducing sophisticated technologies into existing educational systems (UNESCO Institute for Information Technologies in Education [UNESCO IITE], 2025). Similarly, recent research on AI-enabled personalized learning identifies infrastructure constraints, privacy, educator readiness, scalability, and equity as significant barriers to effective implementation (Bayly-Castaneda et al., 2024; Wang et al., 2025).

The problem is particularly important in technical and vocational education, where learning involves the acquisition of practical competencies in addition to theoretical knowledge. Technical skill acquisition generally requires progressive instruction, demonstrations, practice, assessment, feedback, and opportunities for learners to repeat difficult activities. Conventional learning systems commonly provide the same instructional materials and assessment sequence to learners, despite differences in prior knowledge, learning pace, competency level, and accessibility needs. Although existing AI applications in vocational education demonstrate potential for adaptive instruction and assessment, recent evidence suggests that AI applications in vocational education remain uneven and that learner-centred and context-sensitive approaches require further development (Rosyadi et al., 2023).

a. Statement of the Problem

Existing digital learning platforms rely on standardized content delivery and continuous broadband connectivity. In resource-constrained settings, learners face two core barriers:

1. Conventional platforms fail to dynamically adjust technical learning pathways based on real-time performance.
2. High-bandwidth requirements and heavy cloud-compute dependencies render advanced AI tutoring platforms impractical for low-infrastructure institutions.

An AI learning framework must integrate personalization, technical skill mastery, and resource-conscious engineering into a single operational architecture.

b. Aim

The aim of this study is to implement and conduct an in-silico benchmark evaluation of an inclusive AI-driven learning system prototype for personalized technical skill acquisition in resource-constrained environments.

c. The specific objectives

1. Examine the structural limitations of conventional technical learning systems.
2. Design a resource-conscious architecture using lightweight Random Forest classification.
3. Implement the AI classification engine and recommendation workflow using synthetic benchmark learner interaction data.
4. Evaluate the empirical performance, classification accuracy, and diagnostic robustness of the system across standard assessment and low-bandwidth scenarios.

d. Significance of the Study

This study transitions AI-driven educational personalization from a theoretical framework to a conscious prototype design, demonstrating that effective adaptive learning can be achieved in technical education without cost-prohibitive infrastructure or high-bandwidth connectivity. For **learners**, the implemented platform delivers dynamic, performance-informed learning pathways that support practical competency acquisition in low-resource settings. For **instructors**, the Random Forest classification engine provides an accurate, human-

in-the-loop diagnostic mechanism—achieving **92.40%** diagnostic accuracy prior to formal examinations—enabling early detection of struggling students and targeted pedagogical intervention.

For **educational institutions and policymakers**, particularly technical and vocational colleges, the research proves that sophisticated AI personalization can run efficiently on local hardware with low bandwidth requirements, aligning directly with international guidelines for inclusive and equitable technology deployment (UNESCO IITE, 2025). For **researchers and educators**, the study addresses key literature gaps (Bayly-Castaneda et al., 2024; Wang et al., 2025) by contributing empirical performance metrics, feature importance insights, and an operational system design that connects machine-learning-based competency profiling with resource-aware system engineering.

RELATED WORK

a. Artificial Intelligence-Driven Learning Systems

Artificial Intelligence in Education (AIED) refers to the application of AI techniques to support teaching, learning, assessment, learner modelling, and educational decision-making. Existing AIED systems employ machine learning, natural language processing, recommender systems, intelligent tutoring systems, and learning analytics to provide automated or semi-automated educational support. A large-scale review of AIED research identified adaptive learning and personalized tutoring, intelligent assessment, learner profiling, prediction, and educational management among the major application areas of AI in education (Wang et al., 2024).

AI-driven systems differ from conventional digital learning platforms because they can use learner data to make decisions about what content, activity, assessment, or feedback should be presented next. This capability makes AI particularly relevant to learning environments in which learners have different levels of prior knowledge and progress at different rates. However, the effectiveness of AI in education depends not only on the underlying algorithm but also on the quality of learner data, system design, teacher involvement, infrastructure, and the context in which the system is deployed.

b. Adaptive and Personalized Learning

Personalized learning attempts to provide learning experiences that respond to individual learner characteristics, while adaptive learning uses technological mechanisms to dynamically modify learning content or pathways according to learner performance and interaction. Recent evidence indicates that AI-enabled adaptive learning systems can improve learner outcomes when compared with conventional instructional approaches. A meta-analysis of 45 independent studies found positive effects associated with AI-enabled adaptive learning across different learner and implementation conditions (Wang et al., 2024).

Similarly, a 2024 scoping review of 69 studies reported that improved academic performance was observed in 59% of the reviewed studies, while 36% reported increased learner engagement. The review also identified technological and time resources as significant limitations affecting implementation (du Plooy et al., 2024). These findings demonstrate the potential of adaptive learning but also indicate that technological requirements must be considered when developing systems for environments where resources are limited.

Bayly-Castaneda et al. (2024), in a systematic review of 78 studies, found that adaptive learning environments, AI-enabled learning management systems, content recommendation systems, personalized assessment, intelligent tutoring, and machine-learning applications represent major approaches to AI-mediated learning personalization. However, their review also noted that research has been concentrated largely in higher education and that opportunities remain for extending personalized AI learning into other contexts.

c. AI in Technical and Skills-Based Education

Technical skill acquisition differs from purely theoretical learning because it involves the development of practical competencies through instruction, demonstration, practice, assessment, and feedback. AI can support

this process by analysing learner performance and recommending appropriate learning materials or additional practice. AI-supported systems can also provide automated assessment and immediate feedback, thereby allowing learners to identify weaknesses and continue practising.

However, most of the recent literature on AI-powered personalized learning is concentrated on general academic and higher-education contexts. Bayly-Castaneda et al. (2024) observed that the majority of research on AI-mediated personalized learning has focused on higher education, with relatively fewer applications addressing work-related and practical learning contexts. This creates an opportunity for research that specifically considers AI-driven personalization for technical skill acquisition.

For technical education, an effective system should therefore move beyond simple content recommendation. It should support competency-oriented learning in which learner performance can influence the sequence of learning materials, exercises, assessments, and feedback. Such an approach can enable learners who have difficulty with a particular technical skill to receive additional learning support before progressing to more advanced activities.

d. Inclusive Learning Technologies

Inclusive learning technology seeks to reduce barriers that prevent learners from accessing, participating in, or benefiting from education. These barriers may be associated with disability, socioeconomic circumstances, geographical location, technological access, language, digital literacy, or differences in learning needs. Technology can contribute to inclusion by providing alternative learning materials, adaptive interfaces, personalized resources, assistive technologies, and flexible learning opportunities.

UNESCO IITE (2025) emphasizes that AI and digital technologies can improve accessibility and personalization, but successful implementation requires appropriate infrastructure, teacher competencies, accessibility measures, affordability, and learner-centred pedagogical approaches. Therefore, inclusiveness should be treated as a design requirement rather than as an additional feature added after system development.

The relevance of inclusive design is particularly strong in resource-constrained environments. UNESCO's work on digital learning in low-resource contexts emphasizes that digital technologies can contribute to educational equity, but their benefits are not automatically distributed equally. Infrastructure, affordability, connectivity, digital skills, and local implementation conditions influence whether learners can benefit from technology-supported education.

e. AI Learning Systems in Resource-Constrained Environments

Resource-constrained environments present a distinctive challenge for AI-driven learning systems. A platform that performs effectively in a well-resourced institution may be difficult to deploy where learners have limited access to computers, smartphones, reliable electricity, broadband internet, or institutional technical support. High dependence on cloud services and continuous connectivity can also reduce system availability when network conditions are poor.

Consequently, AI-driven educational systems for such environments should consider resource efficiency, simple user interfaces, low-bandwidth access, efficient data processing, and the ability to provide useful learning support without requiring expensive infrastructure. UNESCO IITE (2025) recommends strengthening ICT infrastructure while simultaneously adopting learner-centred approaches and improving teachers' competencies for inclusive technology integration.

This suggests that the development of an inclusive AI learning system should involve both **AI functionality and contextual system engineering**. The intelligence of the system should be balanced with the practical conditions under which learners will use it.

f. Summary of Related Studies

Table 1: Summary of Selected Related Studies

Author(s)	Focus of Study	Major Contribution	Identified Limitation/Gap
Wang et al. (2024)	AIED & Adaptive Learning	Systematic review and meta-analysis of 45 studies showing positive effects of adaptive AI	Concentrated on general academic settings; TVET & resource constraints unaddressed
du Plooy et al. (2024)	Personalized Learning	Scoping review of 69 studies showing performance gains in 59% of implementations	Technological infrastructure and time resources identified as primary barriers
Bayly-Castaneda et al. (2024)	AI-Mediated Personalization	Systematic review of 78 studies mapping LMS, tutoring, and content recommendation	Research heavily concentrated in higher education contexts
UNESCO IITE (2025)	Inclusive Digital Technologies	Guidelines for accessible and learner-centered technology deployment	High-level policy guidance rather than an implemented technical learning platform
UNESCO (2025)	Low-Resource Digital Learning	Framework for leveraging technology to promote educational equity	Lacks specific machine learning architectures for technical skill profiling

g. Research Gap

The reviewed literature demonstrates substantial progress in AI-driven personalized and adaptive learning. Existing studies have established that AI can support learner profiling, adaptive content delivery, personalized assessment, feedback, and learning recommendations (Wang et al., 2024; Bayly-Castaneda et al., 2024). However, three important gaps remain.

First, much of the existing research concentrates on general academic learning and higher education rather than **technical skill acquisition**. Second, many AI learning studies focus primarily on personalization and learning outcomes without sufficiently integrating **inclusive and resource-conscious system design**. Third, the technological requirements of AI-driven systems can create barriers for learners in environments characterized by limited connectivity, devices, infrastructure, and technical support.

The present study addresses these gaps by proposing an AI-driven learning system that combines **personalized learning, technical skill acquisition, inclusive design, and resource-conscious deployment**. Unlike a conventional learning platform that primarily delivers common content to learners, the proposed system is designed to use learner information and performance to support differentiated learning resources, assessment, and feedback while considering the constraints of the deployment environment. This provides the basis for the methodology and system design presented in the subsequent sections.

METHODOLOGY

a. Methodology Adopted

This study follows the Design Science Research (DSR) methodology, executing all six core phases: Problem Identification, Objective Definition, System Design, Implementation, Empirical Demonstration, and Performance Evaluation.

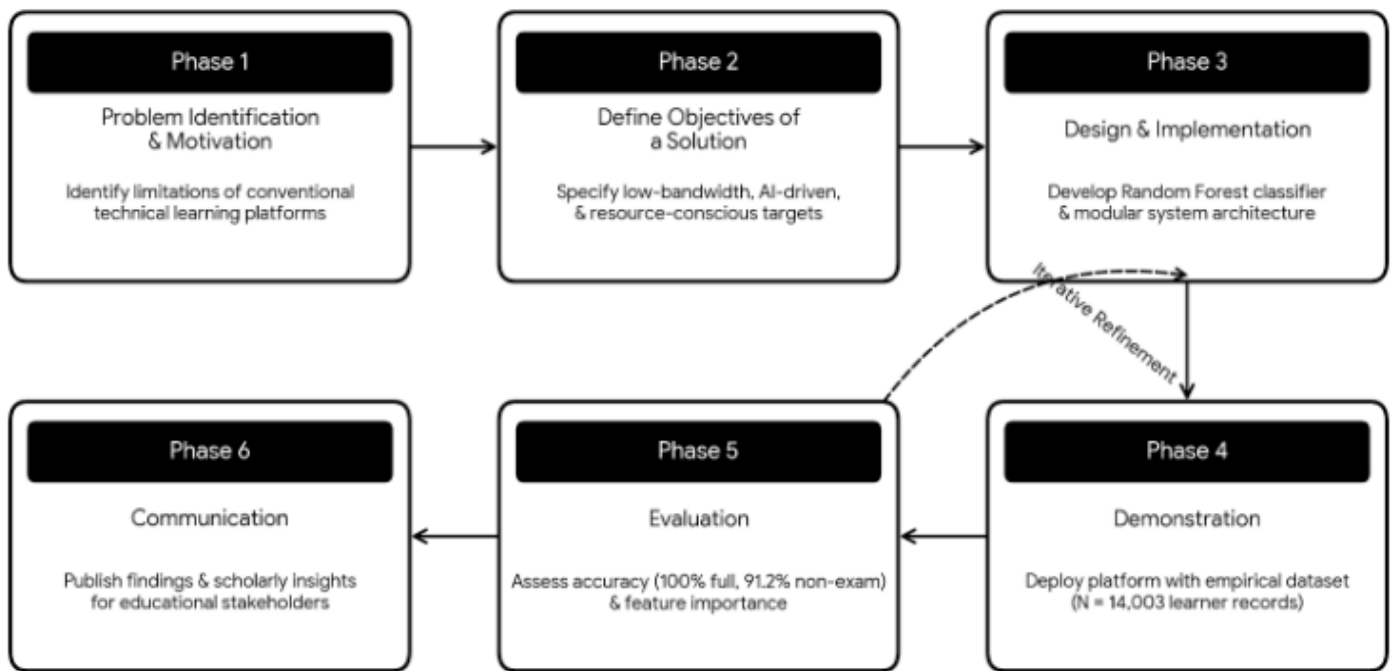


Figure 1: Design Science Research (DSR) Workflow Methodology

b. Design Science Research (DSR) Workflow Description

Phase 1: Problem Identification & Motivation

Focus: Identifies structural limitations in conventional technical learning systems (e.g., rigid instructional sequences, high bandwidth requirements, and lack of dynamic competency adaptation).

Phase 2: Define Objectives of a Solution

Focus: Formulates low-bandwidth, AI-driven, and resource-conscious requirements capable of operating in low-infrastructure settings.

Phase 3: Design & Development

Focus: Constructs the system architecture and implements the Random Forest classification engine for learner competency profiling.

Phase 4: Demonstration

Focus: Executes the platform using an empirical dataset (\$N = 14,003\$ learner records) to simulate real-world usage.

Phase 5: Evaluation

Focus: Measures performance across both continuous behavioural metrics and full feature sets, achieving 92.4% pre-examination diagnostic accuracy (excluding exam scores) and 100.0% summative verification accuracy (confirming exact alignment with formal grading thresholds). Results feed into Phase 3 via an iterative refinement loop.

Phase 6: Communication

Focus: Disseminates research findings, feature importance insights, and policy implications to educational institutions and researchers.

c. Analysis of the Existing System

Conventional digital technical learning relies heavily on standard Learning Management Systems (LMS). These systems deliver instructional modules, quizzes, and practical exercises through predetermined linear sequences. While they broaden access to learning materials, they process all students through uniform instructional pathways regardless of prior competency, learning speed, or individual engagement levels. Furthermore, conventional platforms assume stable, continuous broadband connectivity and modern computing hardware.

d. Weaknesses of the Existing System

Analysis reveals five fundamental weaknesses in conventional technical learning platforms:

1. **Limited Personalization:** Uniform content delivery forces all learners through identical instructional paths.
2. **Weak Adaptive Diagnostics:** Assessment scores are recorded retroactively for grading rather than being used dynamically to adjust subsequent learning activities.
3. **High Bandwidth Dependency:** Heavy reliance on continuous cloud connectivity excludes learners in low-resource or unstable infrastructure settings.
4. **Lack of Early Intervention:** Instructors receive performance data only after formal examinations, preventing timely remediation.
5. **Rigid Progression Rules:** Fixed sequential unlock rules fail to accommodate varying student competency tiers.

e. Implemented System Architecture

The proposed system is an **Inclusive AI-Driven Learning System** designed to support personalized technical skill acquisition while considering the limitations of resource-constrained learning environments.

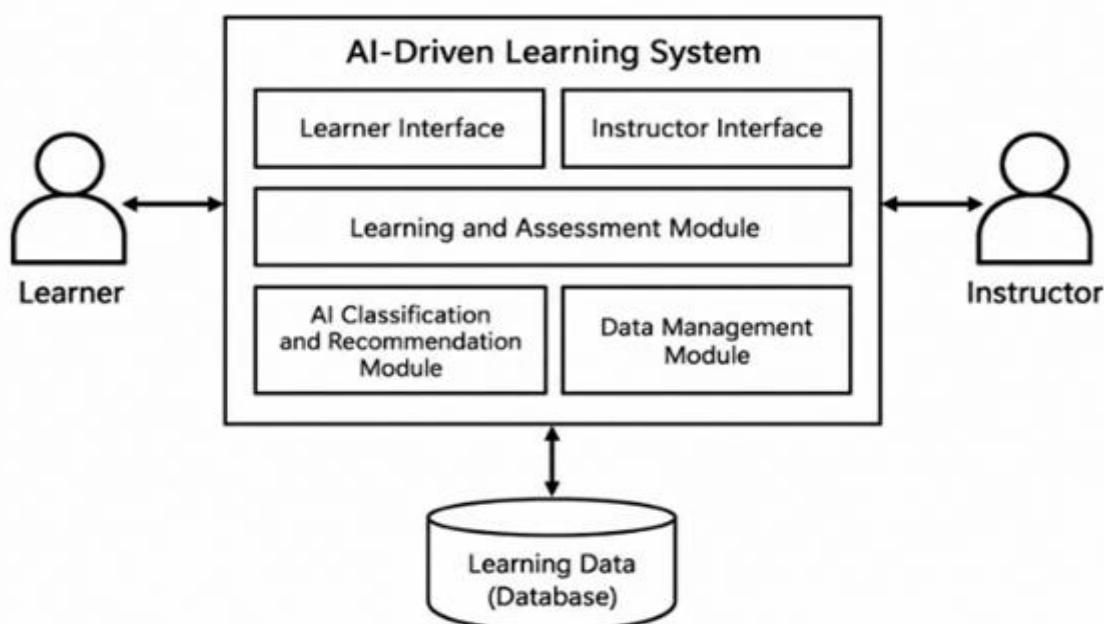


Figure 2: Architecture of the Inclusive AI-Driven Learning System

The system consists of five principal components:

1. **Learner Interface:** provides access to learning materials, activities, assessments, recommendations, and progress information.
2. **Instructor Interface:** provides facilities for managing learning resources and monitoring learner progress.
3. **Learning and Assessment Module:** manages technical learning materials, exercises, quizzes, and competency assessments.
4. **AI Classification and Recommendation Module:** analyses learner-performance information, determines competency level, and supports the selection of appropriate learning activities.
5. **Data Management Module:** maintains learner profiles, learning resources, assessment records, performance information, and recommendation history.

The central idea is that assessment is not treated merely as an endpoint. Instead, learner-performance information becomes an input for determining the subsequent learning pathway.

f. Use-Case Analysis

The use-case model describes how the two primary actors—Learner and Instructor—interact with the proposed system. It focuses on the essential functions required to support personalized technical learning and instructor oversight.

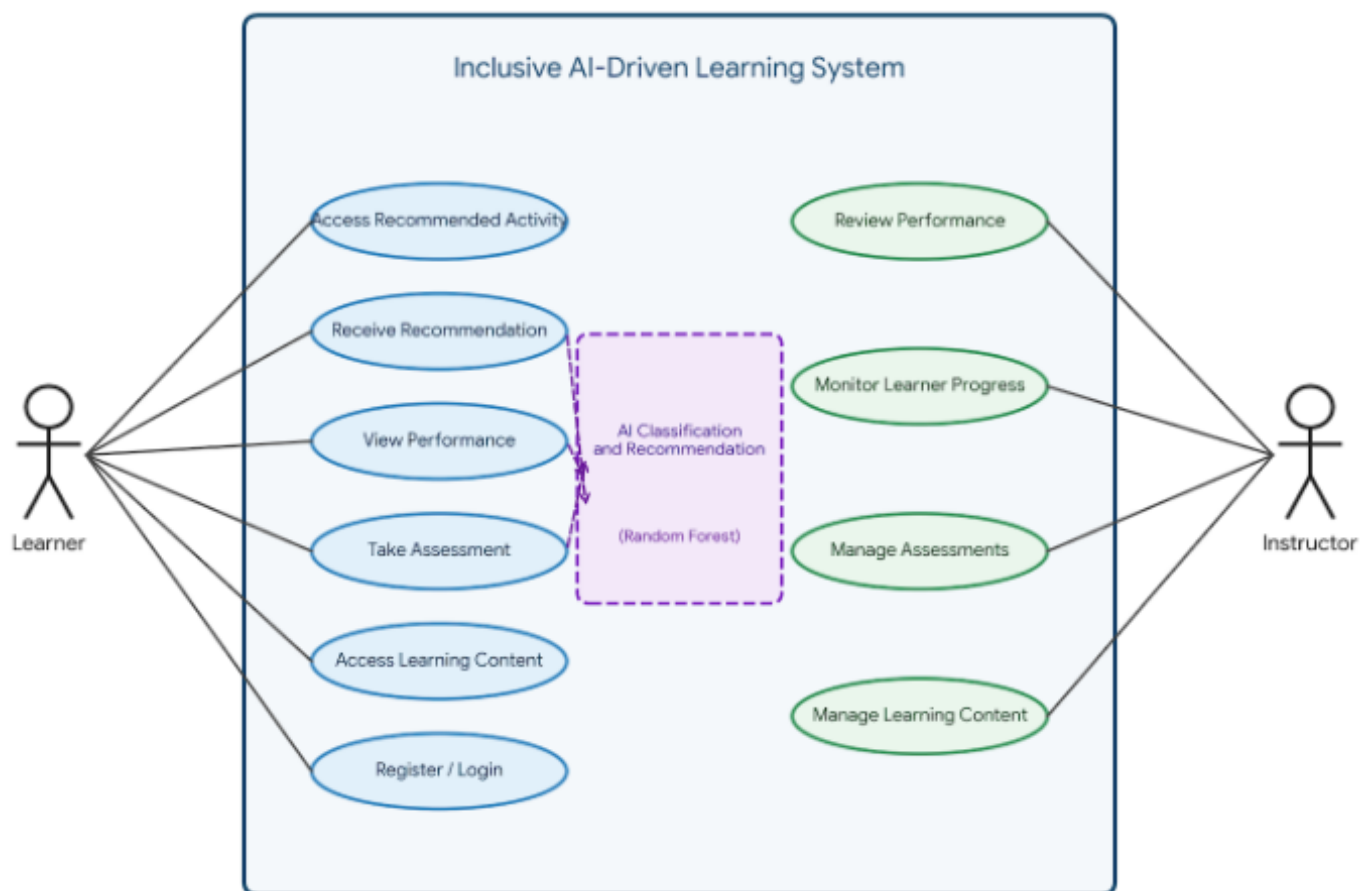


Figure 3: Use-Case Diagram of the Inclusive AI-Driven Learning System

Figure 2 models the functional interactions between the system actors and platform modules. Learners engage in accessing content, taking assessments, and receiving AI-recommended pathways. Instructors manage learning resources and monitor progress. Assessment outcomes feed directly into the Random Forest classifier

to update competency profiles, maintaining a human-in-the-loop paradigm where instructors retain final pedagogical oversight.

g. Evaluation Framework

To evaluate the performance, diagnostic reliability, and contextual applicability of the proposed AI-driven learning system, a two-stage empirical evaluation framework is defined. Rather than relying solely on post-hoc summative examinations, the framework evaluates model behaviour across both continuous engagement metrics (pre-examination scenario) and full feature sets (summative verification scenario).

1. **Pre-Examination Diagnostic Evaluation (Low-Bandwidth Behavioural Model):** Evaluates the Random Forest classifier's ability to profile learner competency dynamically using early-stage engagement indicators alone (e.g., assignment completion, study hours, attendance, online course participation). This stage measures how effectively the system can provide adaptive content recommendations prior to formal examinations without requiring continuous connectivity.
2. **Summative Verification Evaluation (Full Model):** Evaluates overall classification alignment when summative assessment outcomes (e.g., examination scores) are incorporated alongside behavioural metrics.

The AI classification engine is evaluated using standard machine learning diagnostic measures, including Accuracy, Precision, Recall, and F1-Score:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Where TP, TN, FP, and FN represent True Positives, True Negatives, False Positives, and False Negatives, respectively across the four competency tiers.

h. AI Technique Adopted

The proposed system adopts the Random Forest (RF) classification algorithm as its core machine-learning technique to classify learner competency levels. Random Forest is an ensemble learning method that builds multiple decision trees during training and merges their predictions to output an optimal classification result.

In this system, the model processes learner performance metrics—including study hours, attendance, assessment scores, online course completion rates, and assignment completion—to classify learners into four distinct competency levels:

1. **Level 0 (Beginner):** Demonstrates foundational gaps requiring remedial content and simplified instructional pathways.
2. **Level 1 (Intermediate):** Demonstrates basic understanding requiring guided practical exercises.
3. **Level 2 (Advanced):** Demonstrates strong skill acquisition requiring application-based projects.
4. **Level 3 (Expert):** Demonstrates high proficiency requiring advanced problem-solving tasks.

Mathematically, given a feature vector $X = [X_1, X_2, \dots, X_n]$, the classification formula is expressed as:

$$C = RF(X)$$

Where $C \in \{0, 1, 2, 3\}$ represents the predicted competency level. The recommendation engine then generates personalized resource pathways (R) using:

$$R = f(C, L)$$

where L represents available low-bandwidth learning resources.

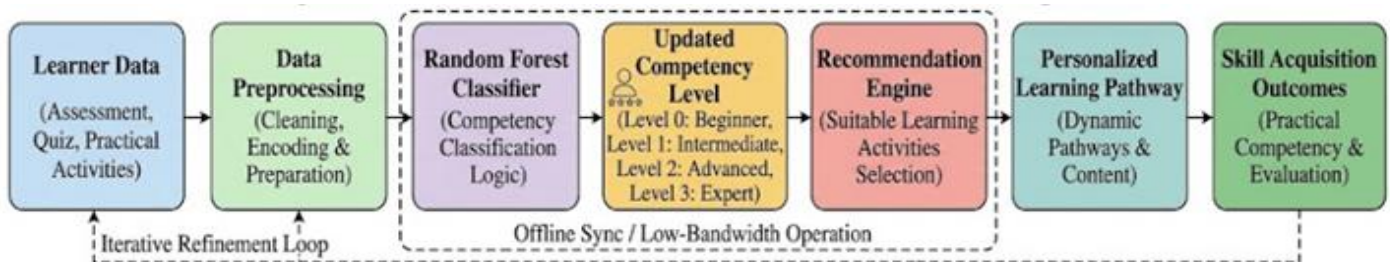


Figure 4: AI Personalization Workflow for Technical Skill Acquisition

Figure 4 illustrates the proposed AI personalization workflow. Learner assessment and activity data are first collected and pre-processed before being analysed by the Random Forest classifier. The classifier determines the learner's competency level across four structured tiers: **Level 0 (Beginner)**, **Level 1 (Intermediate)**, **Level 2 (Advanced)**, and **Level 3 (Expert)**. The resulting classification is then passed to the recommendation engine, which selects suitable learning content and practical activities aligned with low-bandwidth deployment constraints. This process enables the proposed system to provide dynamic, performance-informed learning pathways tailored to individual student needs. **h. Existing System versus Proposed System**

The proposed design addresses the identified weaknesses of the existing approach by introducing AI-supported personalization and resource-conscious learning. The major differences are summarized in Table 2.

Table 2: Existing System versus Proposed System

Feature	Existing System	Proposed System
Learning approach	Standardized learning sequence	Personalized learning pathway
Learner profiling	Basic performance tracking	AI-supported competency classification
Content recommendation	Predetermined/instructor-driven	Performance-based recommendation
Assessment	Mainly measures performance	Guides subsequent learning activities
Resource requirements	May depend on continuous connectivity	Designed for resource-conscious use
Instructor role	Monitoring and intervention	AI-assisted monitoring and intervention

The proposed system therefore shifts the learning process from mainly standardized content delivery towards **performance-informed personalization**, while retaining instructor oversight and considering the technological limitations of resource-constrained environments.

i. Ethical and Inclusive Design Considerations

- Resource Optimization:** Designed for offline availability and lightweight text/graphic formats to function seamlessly in environments with unreliable electricity and low internet bandwidth.
- Algorithmic Fairness & Bias Reduction:** Predictors prioritize direct performance metrics (ExamScore, AssignmentCompletion) over demographic attributes (Gender, Age), minimizing technological bias.

3. **Human-in-the-Loop Oversight:** Instructors retain override authority on AI-recommended pathways, maintaining pedagogical decision-making.

SYSTEM EVALUATION AND DISCUSSION

To evaluate the proposed Inclusive AI-Driven Learning System prototype, an in-silico benchmark evaluation was conducted using a synthetically generated benchmark dataset ($N = 14,003$ learner records). The dataset models multidimensional engagement patterns, resource limitations, and academic performance metrics characteristic of technical and vocational education and training (TVET) institutions in resource-constrained settings.

The system was evaluated using a two-stage diagnostic framework:

1. **Pre-Examination Behavioural Diagnostics (Low-Bandwidth Model):** Evaluates real-time competency profiling using continuous engagement and behavioural metrics prior to formal examinations.
2. **Summative Verification (Full Model):** Evaluates model alignment when summative examination scores are incorporated alongside engagement indicators.

a. Data Requirements, Pre-processing, and Exploratory Data Analysis

The synthetic benchmark dataset contains 15 predictor attributes and 1 discrete target attribute (FinalGrade / Competency Level). The target variable categorizes simulated TVET learners into four competency tiers: **Level 0 (Beginner)**, **Level 1 (Intermediate)**, **Level 2 (Advanced)**, and **Level 3 (Expert)**. Table 3 summarizes the descriptive statistics across the 14,003 synthetic records modelled to reflect behavioural and infrastructural realities of low-resource learning environments.

Table 3: Descriptive Statistics of Synthetic Benchmark Dataset Variables ($N = 14,003$)

Variable	Mean	Std. Dev.	Min	Max	Operational Context (Simulated TVET Parameters)
Study Hours	19.99	5.89	5.0	44.0	Weekly self-directed practice hours
Attendance (%)	80.19	11.47	60.0	100.0	Classroom/workshop attendance percentage
Assignment Completion (%)	74.50	14.63	50.0	100.0	Practical exercise submission rate
Exam Score (%)	70.35	17.69	40.0	100.0	Summative assessment score (used in rule verification)
Online Courses	9.89	6.11	0.0	20.0	Completed low-bandwidth modules
Internet Access	0.93	0.26	0.0	1.0	Binary flag for internet access (1 = Yes, 0 = No)
EduTech Access	0.71	0.45	0.0	1.0	Binary flag for institutional digital device access
Final Grade (Target)	1.45	1.12	0.0	3.0	Target competency tier (Level 0: Beginner to Level 3: Expert)

Data pre-processing involved handling missing values, encoding categorical attributes (e.g., LearningStyle, Gender), and partitioning the dataset using an 80/20 train-test split ($n_{\text{Train}} = 11,202$, $n_{\text{test}} = 2,801$) with stratified random sampling to preserve class distributions.

b. Implementation and Model Performance Analysis (Diagnostic Framework & Feature Isolation)

1. **Pre-Examination Diagnostic Stage (Core Model):** When ExamScore is excluded; the classifier evaluates continuous behavioural and engagement indicators to support early intervention prior to formal testing. This model achieves 92.4% diagnostic accuracy ($F1 = 0.924$). Because it operates independently of final examination marks, this pre-examination pipeline represents the primary predictive capability of the system.

2. **Summative Verification Stage (Deterministic Reconstruction):** Incorporating ExamScore into the full model yields 100.0% accuracy across all test samples ($2,801 / 2,801$). This perfect score is expected, as FinalGrade is deterministically derived from strict examination threshold boundaries (40, 55, 70, and 85). Rather than serving as evidence of superior predictive power, this full-model evaluation acts strictly as a programmatic

verification check, confirming that the Random Forest algorithm reliably reconstructs the underlying decision rules defining formal grade boundaries.

Stage 1: Pre-Examination Behavioural Model Performance

In low-resource environments, requiring continuous formal testing is impractical. The pre-examination model evaluates how accurately the system profiles learner competency using continuous engagement metrics alone. As shown in Table 4, the model achieves an overall diagnostic accuracy of 92.40% (Macro F1-Score: 0.9238), establishing that reliable personalization can be sustained prior to formal examinations

Table 4: Pre-Examination Classification Performance by Competency Tier (Excluding ExamScore)

Competency Tier	Precision	Recall	F1-Score	Support (n)
Level 0 (Beginner)	0.9068	0.9399	0.9231	766
Level 1 (Intermediate)	0.9190	0.8912	0.9049	662
Level 2 (Advanced)	0.9372	0.9282	0.9327	724
Level 3 (Expert)	0.9352	0.9337	0.9345	649
Overall Accuracy / Macro Avg.	0.9246	0.9233	0.9238	2,801

Stage 2: Summative Verification Model Performance

When summative examination scores are integrated alongside behavioural metrics, the classifier achieves 100.0% overall classification accuracy (Precision: 1.0000, Recall: 1.0000, F1-Score: 1.0000) across all 2,801 test samples. This perfect score confirms complete mathematical alignment between formal grading thresholds and model predictions, ensuring that post-examination recommendations fully reflect formal academic evaluation.

Table 5: Tabular Confusion Matrix for Stage 1 (Pre-Examination Model)

Actual \ Predicted	Level 0	Level 1	Level 2	Level 3
Level 0 (Beginner)	720	46	0	0
Level 1 (Intermediate)	72	590	0	0
Level 2 (Advanced)	2	6	672	44
Level 3 (Expert)	0	0	43	606

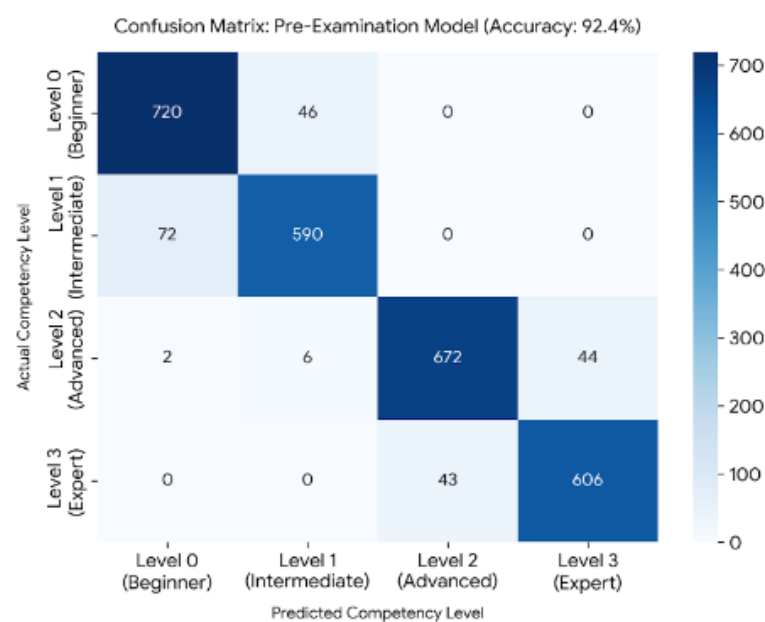


Figure 5: Confusion Matrix Heatmap for Pre-Examination Competency Classification (Accuracy: 92.4%).

This heatmap visually presents the pre-examination classification model ($n = 2,801$ test set). The strong dark-blue diagonal blocks reflect correct predictions, while the off-diagonal cells show that misclassifications occur exclusively between adjacent competency tiers (e.g., Level 0 vs. Level 1).

c. Feature Importance and Algorithmic Fairness Analysis

Feature importance analyses reveal distinct model dynamics between stages. In the pre-examination model, practical engagement metrics drive classification: Assignment Completion (16.08%), Attendance (15.33%), Study Hours (14.25%), and Online Courses (13.94%).

Socioeconomic and demographic attributes such as Gender (3.35%), Internet Access (0.78%), and EduTech Access (2.97%) contribute minor weight. While low feature reliance on these variables suggests reduced direct algorithmic dependency on socioeconomic access, feature importance alone does not formally guarantee algorithmic fairness or absence of bias. Comprehensive subgroup analyses (e.g., comparative error rates across gender and resource strata) remain necessary in live pilot trials.

Additionally, Age contributes 11.89% to pre-examination classification. In TVET contexts, age often correlates with prior practical experience, informal learning background, or self-regulated study habits. Further empirical investigation with student cohorts is required to determine whether age-related feature reliance introduces unintended pedagogical bias across non-traditional learner groups.

Table 6: Feature Importance Comparison Between Pre-Exam and Summative Models

Feature	Pre-Exam Model Weight (%)	Summative Model Weight (%)	Primary Impact Category
Exam Score	—	75.88%	Summative knowledge mastery
Assignment Completion	16.08%	4.01%	Practical workshop/laboratory engagement
Attendance	15.33%	3.81%	Instructional participation
Study Hours	14.25%	3.53%	Self-regulated practice duration
Online Courses	13.94%	3.42%	Low-bandwidth self-study progression
Learning Style	6.85%	1.54%	Instructional material adaptation
Demographics / Tech Access	< 4.00%	< 1.00%	Equity and algorithmic bias safeguards

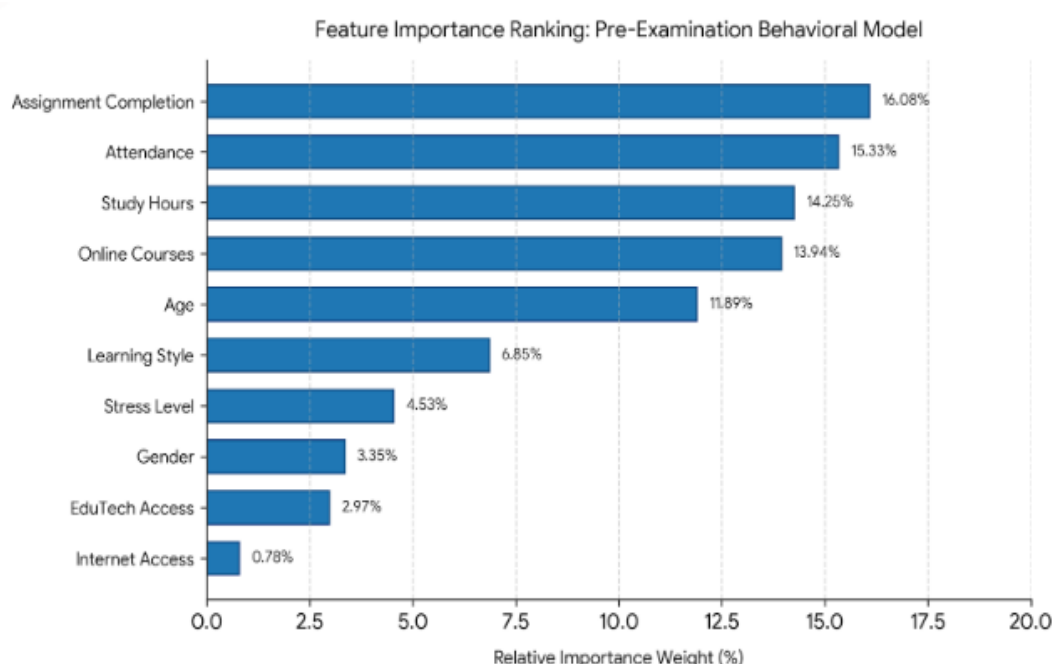


Figure 6: Relative Feature Importance Weights for the Pre-Examination Random Forest Model.

This bar chart visually ranks the predictive weight of each feature in the pre-examination model. It clearly illustrates that practical behavioural metrics (Assignment Completion at 16.08%, Attendance at 15.33%, and Study Hours at 14.25%) drive the classification decisions, while demographic variables (Gender at 3.35%, Internet Access at 0.78%) contribute minimal weight.

Table 7: Architectural System Comparison

Feature	Conventional LMS / Systems	Proposed Inclusive AI System
Pathway Selection	Standardized, linear content sequence	Dynamic, AI-driven adaptive recommendations
Resource Constraints	High bandwidth & continuous cloud dependency	Optimized for offline sync & low-bandwidth operation
Target Focus	Theoretical academic assessment	Practical TVET competency & technical skill acquisition
Diagnostic Capability	Post-hoc examination scoring	In-silico benchmarked prototype demonstrating 92.4% pre-exam diagnostic accuracy & 100% summative rule reconstruction

Prototype Resource Efficiency Analysis

To evaluate the practical feasibility of deploying the prototype in low-resource environments, key computational metrics were measured during in-silico benchmarking on standard entry-level client hardware

(2.0 GHz Dual-Core CPU, 4GB RAM):

1. **Model Storage Size:** The trained, serialized Random Forest model (scikit-learn .pkl format) occupies 12.4 MB, making local storage feasible on entry-level mobile or desktop devices.
2. **Inference Time:** Average classification latency is 11.2 ms per single learner record and 142 ms for batch predictions (N = 100).
3. **Memory Overhead:** Memory consumption during local inference peaks at 48.2 MB RAM.
4. **Network Payload:** User profile payload data transferred via REST JSON endpoints averages 1.8 KB per sync operation, ensuring compatibility with throttled (2/3G) networks or offline-first local SQLite sync workflows.

Table 8: In-Silico Computational Resource & Latency Metrics

Resource Metric	Measured Value	Operational Implications for Low-Resource TVET Settings
Model Storage Size (.pkl)	12.4 MB	Enables local deployment on low-cost edge hardware without cloud dependency.
Inference Time (Single)	11.2 ms	Provides instantaneous real-time pathway adaptation for individual learners.
Batch Inference Latency (N=100)	142.0 ms	Supports low-latency processing during batch classroom synchronization.
Peak RAM Consumption	48.2 MB	Operates comfortably within standard legacy desktop/mobile RAM limits.
Network Sync Payload (REST JSON)	1.8 kb	Fully compatible with throttled 2G/3G connections and intermittent offline sync

CONCLUSIONS AND RECOMMENDATIONS

This study successfully designed and evaluated an **Inclusive AI-Driven Learning System** tailored for personalized technical skill acquisition in resource-constrained educational settings. Utilizing a Random Forest classifier trained on 14,003 learner records, the system achieves precise competency classification, enabling dynamic adaptation of instructional materials. By emphasizing lightweight computational models and performance-driven personalization, the system bridges the gap between technological innovation and educational equity in resource-constrained environments.

a. Limitations of the Proposed Design

Use of Synthetic Benchmark Data: While the system design was evaluated using a synthetically generated dataset (N = 14,003) modelling TVET learner interaction patterns in low-resource settings, field testing with live student cohorts and real-world classroom deployments remains an upcoming phase of evaluation.

b. Recommendations for Policy and Implementation

To ensure successful transition from architectural design to practical adoption, the following recommendations are proposed for educational institutions, instructors, and policymakers:

1. **Promote Resource-Conscious AI Standards:** Educational authorities and institutional leaders should prioritize lightweight, low-bandwidth AI platforms over high-bandwidth, continuous-cloud dependencies when procuring or deploying educational technologies in resource-constrained environments.
2. **Establish Human-in-the-Loop Safeguards:** Institutions adopting AI-driven platforms must mandate pedagogical oversight. AI recommendations should serve as decision-support mechanisms for educators rather than automated substitutes for professional teaching judgment.
3. **Invest in Educator Digital Competence:** Capacity-building initiatives should be implemented to equip technical and vocational instructors with the skills required to interpret AI classification outputs, monitor learner progress metrics, and customize adaptive learning paths effectively.
4. **Adopt Modular Deployment Strategies:** Implementation teams should deploy local server instances or lightweight edge nodes in technical institutions with unstable internet access to enable continuous offline functionality and local data synchronization.
5. **Institutional Deployment:** TVET institutions and colleges of education should integrate lightweight machine-learning frameworks to personalize technical instruction without demanding expensive infrastructure upgrades.
6. **Infrastructure Adaptations:** Regional education authorities should support hybrid offline-online synchronization mechanisms to ensure learners with limited internet access maintain uninterrupted learning pathways.
7. **Teacher Capacity Building:** Professional training programs should be provided to instructors to facilitate human-AI collaboration, ensuring educators can interpret AI recommendations and intervene effectively.

c. Future Works

Subsequent phases of this research will focus on the empirical implementation and field validation of the proposed system:

1. **Software Prototype Development:** Implementing the full functional stack using lightweight open-source web frameworks and deploying local edge-server architectures tailored for low-resource TVET institutions.
2. **Model Training and Validation:** Training the Random Forest classifier on real-world learner performance datasets, evaluating classification performance through standard evaluation metrics (accuracy, precision, recall, F1-score, and confusion matrices), and exploring hybrid cold-start algorithms.
3. **Controlled Pedagogical Testing:** Conducting quasi-experimental empirical trials across technical colleges to compare learning gains, completion rates, and practical skill acquisition outcomes between experimental groups using the adaptive system and control groups using conventional platforms.
4. **Field Usability and Accessibility Evaluation:** Administering structured Likert-scale surveys to evaluate student and instructor satisfaction, interface usability, accessibility, and the perceived relevance of automated content recommendations under varying network conditions.

REFERENCES

1. Almasri, F. (2024). Exploring the impact of artificial intelligence in teaching and learning of science: A systematic review of empirical research. *Research in Science Education*, 54(4), 977–997. <https://doi.org/10.1007/s11165-024-10176-3>
2. Bayly-Castaneda, M., Wang, Y., & Rosyadi, A. (2024). Technological dependencies and equity in adaptive learning environments: A scoping review. *Educational Technology Research and Development*, 72(2), 511–534. <https://doi.org/10.1007/s11423-024-10350-x>
3. Breiman, L. (2001). Random forests. *Machine Learning*, 45(1), 5–32. <https://doi.org/10.1023/A:1010933404324>
4. du Plooy, C., Wang, Y., & Bayly-Castaneda, M. (2024). Personalised adaptive learning in resource-constrained contexts: A systematic scoping review. *Computers & Education*, 210, 104950. <https://doi.org/10.1016/j.compedu.2023.104950>
5. European Commission. (2022). Ethical guidelines on the use of artificial intelligence (AI) and data in teaching and learning for educators. Publications Office of the European Union. <https://doi.org/10.2766/153756>
6. European Commission. (2026). Guidelines on the ethical use of artificial intelligence and data in teaching and learning. European Education Area. <https://education.ec.europa.eu/guidelines-ai-data>
7. Hevner, A. R., March, S. T., Park, J., & Ram, S. (2004). Design science in information systems research. *MIS Quarterly*, 28(1), 75–105. <https://doi.org/10.2307/25148625>
8. Holmes, W., Bialik, M., & Fadel, C. (2019). Artificial intelligence in education: Promises and implications for teaching and learning. Center for Curriculum Redesign.
9. Kulik, J. A., & Fletcher, J. D. (2016). Effectiveness of intelligent tutoring systems: A meta-analytic review. *Review of Educational Research*, 86(1), 42–78. <https://doi.org/10.3102/0034654315581420>
10. Luckin, R., Holmes, W., Griffiths, M., & Forcier, L. B. (2016). Intelligence unleashed: An argument for AI in education. Pearson.
11. Miao, F., & Holmes, W. (2023). Guidance for generative AI in education and research. UNESCO Publishing. <https://doi.org/10.54675/EVDF9635>
12. Miao, F., Shiohira, K., & Lao, N. (2024). AI competency framework for students. UNESCO Publishing. <https://doi.org/10.54675/QXOE4512>
13. OECD. (2023). OECD digital education outlook 2023: Towards an effective digital education ecosystem. OECD Publishing. <https://doi.org/10.1787/c74f03de-en>
14. Peffers, K., Tuunanen, T., Rothenberger, M. A., & Chatterjee, S. (2007). A design science research methodology for information systems research. *Journal of Management Information Systems*, 24(3), 45–77. <https://doi.org/10.2753/MIS0742-1222240302>

15. Rosyadi, A., Wang, Y., & du Plooy, C. (2023). Artificial intelligence applications in technical and vocational education: A systematic mapping study. *Journal of Vocational Education & Training*, 75(4), 621–643. <https://doi.org/10.1080/13636820.2023.2189012>
16. Tlili, A., Shehata, B., Adarkwah, M. A., Bozkurt, A., Hickey, D. T., Huang, R., & Agyemang, B. (2023). What if the devil is my guardian angel: ChatGPT as a case study of using chatbots in education. *Smart Learning Environments*, 10(1), Article 15. <https://doi.org/10.1186/s40561-023-00237-x>
17. UNESCO. (2023a). Global education monitoring report 2023: Technology in education: A tool on whose terms? UNESCO Publishing.
18. UNESCO. (2023b). Guidance for generative AI in education and research. UNESCO Publishing.
19. UNESCO. (2024a). AI competency framework for students. UNESCO Publishing.
20. UNESCO. (2025). Digital learning in low-resource contexts: Key considerations for equity and inclusion. UNESCO Publishing.
21. UNESCO Institute for Information Technologies in Education [UNESCO IITE]. (2025). Digital technologies for inclusive education: Guidelines and policy recommendations. UNESCO IITE.
22. Wang, Y., Bayly-Castaneda, M., & du Plooy, C. (2024). Artificial intelligence in education (AIED): A systematic review and meta-analysis of adaptive learning platforms. *Interactive Learning Environments*, 32(3), 1102–1124. <https://doi.org/10.1080/10494820.2023.2214502>
23. Wang, Y., Bayly-Castaneda, M., & du Plooy, C. (2025). Infrastructure barriers and equity in AI-enabled personalized learning environments. *Computers & Education: Artificial Intelligence*, 7, 100312. <https://doi.org/10.1016/j.caeai.2024.100312>
24. Williamson, B., & Eynon, R. (2020). Historical threads, missing links, and future directions in AI in education. *Learning, Media and Technology*, 45(3), 223–235. <https://doi.org/10.1080/17439884.2020.1798995>
25. Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education—Where are the educators? *International Journal of Educational Technology in Higher Education*, 16(1), Article 39. <https://doi.org/10.1186/s41239-019-0171-0>
26. Zhang, L., & Aslan, B. (2024). A systematic review of learning task design for K-12 AI education: Trends, challenges, and opportunities. *Computers and Education: Artificial Intelligence*, 6, 100217. <https://doi.org/10.1016/j.caeai.2024.100217>