

RESEARCH ARTICLE



AI-Enabled Smart Wearable Learning Systems for Personalized Education Through Real-Time Sensing and Learning Analytics Innovation

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Abstract: AI-enabled smart wearable learning systems can be regarded as a new innovative way of offering personalized and adaptive learning experiences by using the sensing and learning analytics capabilities. In the current research, the impact of the AI-enabled smart wearable learning systems on engagement, learning achievement, and instructional innovation is investigated. A sequential explanatory design with mixed methodology was applied with 320 participants and 24 teachers participating. Quantitative data were collected from the use of wearable sensors, questionnaires, pre-tests and post-tests, and learning analytics data from the AI-assisted learning system, while qualitative data came from interviews and focus group discussions. Quantitative data have been analyzed using descriptive statistics, Pearson correlation, multiple regression, and partial least squares structural equation modeling, while qualitative data have been analyzed using thematic analysis. The results showed that academic performance improved from 62.4 in the pre-test phase to 78.6 in the post-test phase. The module completion rate of the system was 86.5%, AI-feedback use was 79.4%, learner engagement was 87.3%, and the accuracy of the wearable sensor was 96.2%. Of academic achievement, student-centered innovation ($\beta = 0.38$) and the effectiveness of learning analytics ($\beta = 0.34$) showed to be statistically the most significant.

Keywords: intelligent wearable learning systems, artificial intelligence, personalized learning, learning analytics, learner-centric innovation

1. Introduction

1.1. Background of the study

The rapid rate of advances in technology has brought about significant changes in approaches to instruction, learning, assessment, and engaging learners in the process. The diversity of learners, the individual learning needs of each one of them, unequal access to learning resources, and the rapid advancement of intelligent technologies have resulted in the demand for a flexible and learner-oriented system [1–3]. Traditional teacher-centered methods of instruction have been criticized because of the standardized nature of their instructional process irrespective of differences in cognitive, cultural, motivational, preferred modes of learning, and acquisition of knowledge by the learners [4]. This is why the integration of artificial intelligence (AI), learning analytics, sensor technologies, and intelligent educational platforms has gained much prominence [5].

The introduction of smart wearables into the learning process has led to the further improvement of the intelligent process of learning. The use of devices that are provided with sensors, communicative interface, and computing abilities has enabled the gathering of information on learner interactions as well as other data pertaining to engagement, behavior, and context [6]. Unlike conventional digital learning systems that need learners to make use of personal computers and mobile phones, smart wearable systems have the ability to create a more continuous and contextual learning experience that enables collecting learner data without disrupting the learning experience.

Therefore, incorporating AI with smart wearables can enable education technology to advance from digitizing learning material into a responsive learning ecosystem. Such a learning system would be able to facilitate learner engagement, motivation, autonomy, academic performance, and accessibility while also helping instructors to understand the individual requirements of the learners.

Personalization becomes particularly important because the needs of learners cannot be treated uniformly. Research has shown that demographic, motivational, and cognitive characteristics have an impact on the learning process and its outcomes [1]. Also, technology-enhanced learning research has found that

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engagement is an important aspect that contributes to good academic achievement and that technologies in education become more effective if learners participate in the process [2].

The advent of the new generation of AI has enabled new prospects in terms of personalized learning. There are some benefits that have been identified by studies examining the attitude of students toward the use of generative AI in education, including personalized support, increased information availability, and flexibility [3]. However, there are ethical issues associated with the integrity of the educational process, dependency on technologies, poor quality of data, and lack of reliability, which means that the incorporation of AI technologies should be based on pedagogical considerations [4, 5].

However, innovative and student-centered education requires paying attention to such issues as student involvement, creativity, collaboration, problem-solving, and creation of knowledge by the learners themselves [6, 7]. It was shown that online learning, as well as learning assisted by technology, is a good tool in this situation [8, 9]. All these tendencies indicate that in the future, intelligent learning systems should not only personalize the learning material but also enable the interaction and active participation of the learners.

The ethical aspect of intelligent education is no less important. The introduction of AI in education raises various questions related to privacy, fairness, transparency, accountability, accessibility, algorithmic bias, and proper management of learners' data [10]. This question becomes particularly urgent when the process of constant observation of learners' activities and interactions takes place through wearable technologies. As a result, the creation of wearable learning systems using AI technologies will involve technological advances along with the ethical issues related to the use of educational data.

Generally, the analysis of the background literature reveals that the transition from teacher-oriented education toward the intelligent learning environment takes place and is characterized by such qualities as personalization and learner-centeredness. However, additional research on ways to combine these concepts in one system should be conducted.

1.2. Problem statement

Even with developments in educational technology, many educational systems do not respond effectively to individual differences in learners' cognition, motivation, engagement, behaviors, and contextual factors [1, 4]. The existing systems currently available tend to provide different functionalities in terms of content delivery, automatic assessment and evaluation, recommendation, tutoring, and content creation [3, 5], yet not having the capacity for sensing the state of the learners and adjusting the teaching approach accordingly. The changes in the state of the learners may, therefore, remain unnoticed and unattended to by the learning system in time.

One more crucial question to answer is how the use of AI-based wearable devices in learning would guarantee equality in education and equal access for learners from diverse socioeconomic, technological, and contextual backgrounds. The issue of the ongoing monitoring of learners through the means of wearable sensors poses further questions related to privacy, security, transparency, and autonomy of learners [10]. Besides, the issue of algorithm-based adaptation may also restrict the autonomy of the learner in case they do not have much influence on decision-making in relation to their education. Thus, it seems to be crucial for the development of an integrated AI-based smart wearable learning system that would combine all the mentioned aspects.

1.3. Literature review

Nevertheless, there are researches that have established the initial framework for future improvements in technology-based, personalized, and intelligent learning. First, researches relating to learner characteristics have identified the impact of demographic and individual differences in learners' strategies and performance [1]. Although the research takes into account the diversity of learners, it fails to consider the continuous sensing and adapting of instruction using AI technologies. This gap can be filled by combining learner profiling and sensing with the use of wearable devices and learning analytics.

Second, researches relating to educational technology have identified the impact of learner engagement on the success of the learning process via technology [2, 11]. In the same way, research relating to learning innovation has emphasized the development of higher-order thinking skills such as critical thinking, creativity, and problem-solving [12]. However, these researches do not offer the mechanisms to continuously monitor the learner state and transform the results into appropriate actions. Therefore, the combination of engagement indicators and AI technology would improve the responsiveness of the educational system [2, 12–19].

Finally, the research on AI has proved the possibilities of automatic assessment, learner profiling, prediction, feedback, instructional support, and educational decision-making [5, 16]. The development of generative AI has extended this potential by adding content creation, tutoring, question answering, and personalized assistance [3, 4, 14]. However, the issues related to reliability, bias in algorithms, lack of transparency and accountability, problems with academic integrity, and too much dependence on automation tools should also be taken into account [5, 10, 14, 16].

Research conducted in the area of blended and online learning has pointed out the role of information technology in facilitating flexible, accessible, and continuous learning [8, 9]. However, researches have also highlighted the fact that technology in itself cannot make the learning process effective because of the need for an instructor, interaction among learners, proper instruction, and pedagogy [8, 13, 19]. Intelligent wearables must complement, but not substitute, traditional pedagogy.

Analytics and machine learning techniques are necessary to understand learner behavior and learning outcomes [11, 15]. Traditional analytics tend to be based on historical data or periodic assessments that are unable to detect rapid changes in the state of learners. Continuous sensing with intelligent wearable technologies could contribute to the collection of richer contextual data for real-time analytics and intervention. Privacy, fairness, transparency, accountability, and inclusivity are the ethical considerations that acquire particular importance in case of continuous sensing of learner data [10, 17, 19].

In general, considerable progress has been made in the fields of personalized learning, AI, digital education, learning analytics, and ethical educational technology [1–5, 8–19]. Nevertheless, research in the abovementioned areas has largely remained fragmented. The purpose of the present study is to solve the identified issue through the development of a smart wearable learning framework.

1.4. Comparative analysis with previous studies

Comparative analysis of the prior research in the field of intelligent education is given in Table 1. In this table, the research theme, contribution, and limitation of each research are provided for the comparison of prior research works within this field. It is seen from the comparison that there is prior research

Table 1
Comparative analysis of existing studies on AI-enabled and wearable-supported intelligent education

Study focus	Major contribution	Major limitation
Learner characteristics [1]	Identified demographic, motivational, and cognitive associate on learning	Did not integrate wearable sensing and AI-based adaptation
Technology-enhanced learning [2]	Established the importance of learner engagement	Primarily focused on engagement rather than continuous wearable monitoring
Generative AI [3, 14]	Demonstrated personalized support and content-generation capabilities	Concerns remain regarding integrity, reliability, and responsible use
AI in education [5, 16]	Demonstrated potential for personalization and automation	Limited integration with wearable sensing
Smart wearable learning [6]	Highlighted real-time sensing and contextual learning	Limited evidence concerning educational equality and long-term outcomes
Student-centered innovation [6, 7]	Emphasized learner participation and creativity	Does not provide a comprehensive AI-wearable architecture
Online/blended learning [8, 9, 13]	Demonstrated flexibility and accessibility of digital education	Technology-mediated learning does not necessarily provide continuous personalization
Learning analytics [11, 15]	Supported predictive modeling and adaptive decision-making	Often relies on conventional digital learning data rather than multimodal wearable data
AI ethics [10]	Identified privacy, fairness, transparency, and accountability requirements	Limited practical integration into wearable adaptive learning frameworks

on various fields of intelligent education including learner characteristics, technology-enabled learning, generative AI, AI in education, smart wearable learning, student innovation, online learning and blended learning, learning analytics, and AI ethics.

Prior research on each field of intelligent education exists. However, these researches have various perspectives on technology and research.

From this comparison, one can see that although earlier researchers have made some solid foundations, they have separately studied topics such as AI, wearables, learning analytics, pedagogy, and educational ethics.

1.5. Literature synthesis

It is clear from the above literature review that there has been a move from the traditional standard teaching method to a personalized teaching method. Three main themes can be recognized.

First, the personalized nature of learning is considered a necessary condition for successful education since learners are different from each other in terms of cognitive, motivational, demographic, behavioral, and environmental factors [1, 4].

Second, intelligent technologies like AI, learning analytics, and wearable sensors have the technical capability to monitor the state of the learner and make adaptive decisions [5, 6, 9, 15].

Also, a human-oriented and ethical approach is of critical significance. Technologies of education must be developed not only in terms of learner engagement, autonomy, accessibility, and equity but also learner privacy and ethical use of data [10–13].

All these observations show that the future of the education system should shift from individual applications of technology to the ecosystem of sensing, AI, pedagogy, engagement, and ethics.

1.6. Research gap

However, in spite of the significant number of studies devoted to such topics as artificial intelligence, wearable technology, learning analytics, and personalized learning, many gaps still exist

in this area. First, the gap of integration can be observed because most studies are concerned only with independent research in each of the mentioned areas without any integration framework. Second, the gap of educational equity exists because although there is much attention paid to aspects such as personalization, engagement, and performance, not enough attention is paid to ensuring equitable access to learning. Third, there is a gap in real-time adaptation since educational systems are mostly based on past data and regular evaluations, but not on the continuous sensing and timely AI interventions provided by wearables. Fourth, there is a gap of ethical data management, as there is no proper embedding of privacy, fairness, transparency, and accountability in practical applications of AI-wearable learning architecture. Fifth, the gap of learner agency is present as adaptive systems tend to be based on algorithm optimization, not on learner agency to accept, modify, or reject AI interventions. Finally, there is a gap in pedagogical integration since there is a lack of evidence about sustainable integration of AI-enabled wearable technologies into class practices.

1.7. Novelty of the study

What is unique about this research is the development of the intelligent wearable learning system using AI that involves wearable sensors, AI, learning analytics, learner profiling, adaptability-based decision-making, personal intervention, and human-centered learning as a whole. Existing studies have been carried out only on different aspects of these processes individually; however, the proposed study will be aimed at developing the process of learner sensing, data collection, AI-based analysis, personal intervention, feedback for the learners, and improvement of the system. Educational equity, accessibility, learner autonomy, behavioral interaction, motivation, engagement, and data ethics are considered key components of intelligent learning and, thus, the focus of the proposed system. This means that the research is going beyond traditional models restricted to the performance of the learner.

1.8. Aim and objectives of the study

The purpose of this research is to develop and evaluate an intelligent wearable learning system based on AI, which would make it possible to implement a learner-centered, personalized, adaptive, and inclusive education system using wearable technologies, AI, learning analytics, and intelligent pedagogical support. Specifically, this research is going to look at recent trends related to smart wearable learning systems, their influence on personalized learning, motivation of learners, autonomy of learners, accessibility, and academic achievements of learners.

2. Research Methodology

2.1. Research design

A sequential explanatory mixed method research design was used in the current study in order to investigate the connections between AI-driven smart wearable learning systems, real-time sensing, learning analytics, personalized learning, learner engagement, and academic success. In this design of the study, the quantitative phase was conducted first and followed by the qualitative phase so that the study could first measure the learning outcomes and then understand the context behind the quantitative results.

Numeric data were collected in the quantitative phase by employing wearable sensing, structured questionnaires, academic tests, and learning analytics. Data collected via wearable sensing included physiological measures, behavior indicators, and engagement indicators, whereas data from structured questionnaires included information about learners' experience, system usability, technology acceptance, satisfaction, and personalized learning and education equity. Academic performance was measured by

pre- and post-tests, whereas learning analytics included data on the learning process, participation, on-task time, feedback use, and personalized learning experiences. Descriptive statistics, Pearson correlation, multiple regression analyses, partial least squares structural equation modeling (PLS-SEM), and paired-sample *t*-tests were used to analyze variables, interrelations between them, and their effect.

The qualitative stage was conducted after the quantitative stage and involved interviewing teachers and focus group discussions with learners. Qualitative data were analyzed using thematic analysis to gain a better insight into participants' experience with regard to personalization, feedback, engagement, usability, technology adoption, privacy, and instruction design. The results obtained via both approaches were synthesized to develop a picture of the AI-enabled smart wearable learning environment. In general, the methodology provides an evidentiary base for assessment of personalized education through real-time sensing and learning analytics. Figure 1 illustrates the methodology framework.

An example of a smart wearable learning environment using AI is shown in Figure 2. The learning environment was designed to offer a personalized learning experience through real-time sensing and learning analytics technology. Physiological, behavioral, and engagement data were gathered through smart wearables such as smartwatches and smart glasses when learners were engaged in learning activities. An analysis using AI technology was conducted on the collected data to measure the level of engagement and attention of learners and their learning requirements.

Figure 3 represents the architecture that constitutes the foundation for the development of the proposed intelligent AI-powered smart wearable learning system. Different types of sensors incorporated into smart wearables provide the capability

Figure 1
Research methodology framework

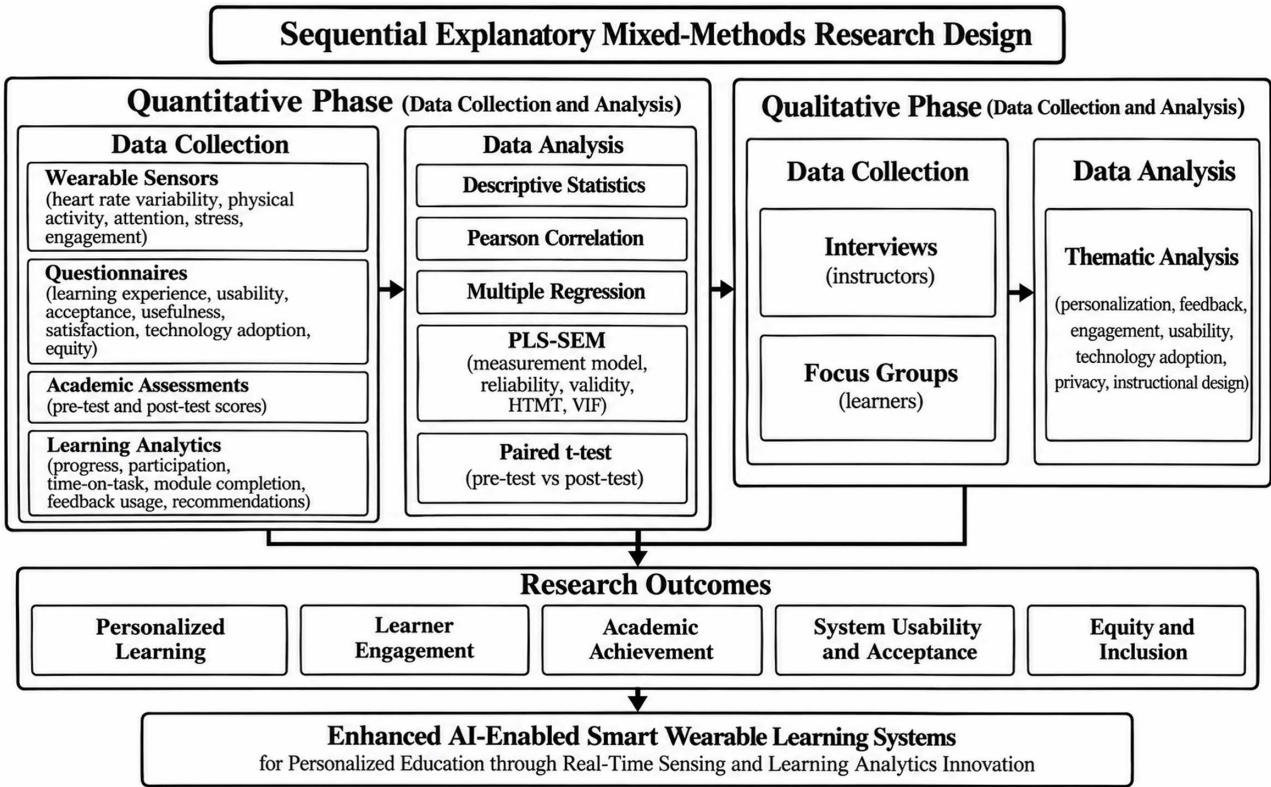


Figure 2
AI-enabled smart wearable learning systems for personalized education through real-time sensing and learning analytics innovation



Figure 3
AI-enabled smart wearable learning architecture for personalized education through real-time sensing and learning analytics



to collect real-time physiological, behavioral, and learning data. IoT is the means for linking the devices to the cloud computing platform where the process of preprocessing, machine learning, and learning analytics occurs. The analysis results provide information through the digital learning interface, which facilitates adaptive and personalized learning.

2.2. Research site, participants and sampling process

The research was carried out in six months’ time frame at two Federal universities in southwestern Nigeria: Federal University

Oye-Ekiti (FUOYE) and Federal University of Technology Akure (FUTA). The research participants consisted of 344 people that were made up of 320 learners and 24 instructors. The learners were PhD students, while the instructors were teachers engaged in the learning process to be evaluated.

The sampling method applied was simple random sampling in order to give all the eligible study population members an equal chance of being selected without introducing any systematic bias. Finally, the learners’ samples had 320 participants and were selected for completing the pre-test and post-test processes. The 24 instructors were selected to participate in the evaluation

of the instructional and implementation process of the AI-based learning environment.

The age of the learners' participants was 30 years and that of the instructors was 40 years. Both the reported learners and instructors were females. The participants and sampling details are shown in Table 2.

FUOYE = Federal University Oye-Ekiti; FUTA = Federal University of Technology Akure.

Criteria for inclusion for learners were active enrollment in the PhD program at one of the participating institutions, being available for participation during the six months' period of the study, willingness to participate in the AI-enabled smart wearable learning tasks, and participation in the required pre-test and post-test evaluations. Those learners who failed to meet the abovementioned criteria were excluded from the analysis of the corresponding data. Instructors were included in the study on the basis of being actively involved in teaching in the participating learning environment.

2.3. Quantitative data collection

Quantitative data collection involved questionnaire responses, results of academic achievement tests, wearable sensor outputs, and learning analytics. The wearable sensors were used to collect physiological, behavioral, and engagement data during the learning process. Before collecting the data, the wearable sensors were calibrated to facilitate accurate data collection.

The measurable variables using the wearable sensors included heart rate variability, physical activities, attention, stress levels, and engagement. Apart from the data collected using the wearable sensors, other data collected included learning experience, system acceptance, perceived usefulness, ease of use, learning satisfaction, and technology adoption from questionnaires. The academic achievement data were collected through pre-test and post-test results. The learning analytics gathered data on learning progressions, participation, time on task, module completion, feedback utilization, and recommendation acceptance.

Quantitative data collection process occurred throughout the entire six-month research period. All 320 learners who participated in the quantitative data collection process underwent pre-tests and post-tests.

The data collection was done systematically through the six-month period according to the sequential explanatory mixed methods design. After recruiting participants and obtaining their

consent, the wearable devices embedded with AI technology were configured and calibrated prior to deployment. Calibration and repeat measurements were done to ascertain the reliability of the physiological, behavioral, and engagement-related data.

The research utilized four major sources of quantitative data including wearable devices, survey questionnaires, academic assessments, and learning analytics. Wearable devices captured physiological, behavioral, and engagement-related data from the participants as they went through the learning experience. A survey questionnaire was used to assess participants' perceptions regarding system usability, technology acceptance, personalized learning, learning satisfaction, instructional quality, and learner engagement. The academic performance of the participants was assessed using pre- and post-test scores, while the learning analytics data were collected from the learning management system and an AI-based learning analytics platform. The learning analytics data were related to learning progress, participation, time on task, feedback utilization, and personalized learning.

The quantitative data were collected at various intervals depending on the measurement tool used. All 320 participants underwent pre- and post-test assessments.

2.4. Analysis of quantitative data

The quantitative data analysis involved the use of descriptive statistics, Pearson correlation, multiple regression, and PLS-SEM. The use of descriptive statistics facilitated the summarization of the demographic characteristics and study variables. On the other hand, the Pearson correlation helped to determine the relationship between AI-based learning experience, real-time learner engagement, learning analytics, student-centered innovation (SCI), perceptions of educational equity, and academic performance. Multiple regression analysis was done to establish the predictive ability of explanatory variables toward learner engagement, personalized learning, and academic performance.

PLS-SEM was used to analyze the relationships between study variables. The measurement model was analyzed using the indicator loadings, Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE). Discriminant validity was tested using a suitable discriminant validity criterion such as the heterotrait-monotrait (HTMT) ratio. Multicollinearity was analyzed using the variance inflation factor (VIF). The measurement-model and discriminant validity findings are presented in the Results section.

Table 2
Participant and sampling characteristics of study participants

Characteristic	Learners	Instructors
Number of participants	320	24
Percentage of total sample	93.0%	7.0%
Age	30 years	40 years
Gender	Female	Female
Participant role	PhD learner	Instructor
Participating institutions	FUOYE and FUTA	FUOYE and FUTA
Number of institutions	2	2
Sampling method	Simple random sampling	Simple random sampling
Study duration	6 months	6 months
Completed pre-test and post-test	320	Not applicable
Total sample	344	

Pre-test and post-test scores were analyzed as paired observations since the same 320 learners completed both measures. Paired test was performed to see if there was any statistically significant difference between the two measures. The observed difference was seen as a relationship to the intervention since the study did not use a separate randomized control group.

2.5. Machine learning analysis

The study measured the predictability of learning using AI-based smart wearables through the application of four machine learning techniques, namely, Random Forest (RF), Support Vector Machine (SVM), Artificial Neural Network (ANN), and Long Short-Term Memory (LSTM). All these models were constructed using data collected from the wearable sensor and learning analytics perspectives.

Before starting training each model, a set of standard procedures for data quality control, preprocessing, and feature extraction was carried out. The last step of the machine learning process comprised clear demarcation of model development and evaluation datasets to avoid any information leakage. If needed, cross-validation was done on the model development dataset only. The final version of the manuscript provides a precise training/test split, cross-validation approach, target variables, predictor variables, and model configuration used during the experiments.

The metrics applied for the assessment of classification performance were accuracy, precision, recall, F1-score, confusion matrices, and Area Under the Receiver Operating Characteristic Curve (AUC-ROC). For continuous predictions, we used mean absolute error (MAE) and root mean square error (RMSE). In the Results section, the results of four separate models—RF, SVM, ANN, and LSTM—are provided to allow comparison of predictive performance.

2.6. Qualitative data collection

The qualitative analysis came after the quantitative analysis of the collected data and helped explain and provide background information about the main findings of the quantitative part of the study. The interview technique was employed to collect information about the experiences of instructors with the use of the smart wearable learning system through semi-structured interviews in order to learn more about the benefits of instruction using such technology, difficulties of its implementation, usability issues, technology adoption, privacy issues, and educational recommendations. This means that the qualitative phase complemented the quantitative data collection methods through the participants' explanations as to how and why the AI-enabled wearable learning environment was experienced in the participating institutions.

The specific number of participants that took part in the interviews and focus groups should be stated separately in the final manuscript according to the qualitative research record. The total number of 344 participants does not mean that all participants participated in each and every qualitative activity.

2.7. Qualitative data analysis

Analysis of the qualitative data collected using the semi-structured interviews and learner focus groups took a thematic form. In the analysis process, there was the step of becoming familiar with the transcripts, identification of important

quotes, open coding, grouping of codes to form categories, theme generation, theme refinement, and finally, interpretation of the themes in light of the quantitative findings and research goals.

Main thematic issues covered personalization, real-time sensing, learning analytics, learner engagement, usability, technology adoption, instructional innovations, privacy, ethics, and implementation challenges. The emerging themes were then compared against the quantitative results to find out where there is congruence, synergy, or divergent findings.

When necessary, the credibility of the thematic interpretation was enhanced through peer review and participant validation of the interpretation. The particular method of validation used in this study is stated here because otherwise, the implication that the participants were validated or the peer review method was used would be raised falsely.

The quantitative data collected through the wearable sensors, questionnaires, academic achievement tests, and learning analytics tools were analyzed using IBM SPSS Statistics and SmartPLS. The processes for data screening, descriptive statistics, correlations, regression, and pre-test post-test analysis were done using SPSS, while the measurement and structural models were estimated using SmartPLS.

2.8. Mathematical formulation of the AI-enabled smart wearable learning system

The mathematical foundation behind the AI-enabled smart wearable learning platform was based on a multimodal, temporal, and adaptive approach for transforming information from physio-behavioral and learning analytics into predictions of the learner's state, performance analysis, and personalization of learning suggestions. The formulation consists of wearable sensing, preprocessing of signals, multimodal feature fusion, state estimation, AI-based calculation, recommendation optimization, and online learning. The complete system could thus be considered as a sequential transformation of the learner's sensed information into an adaptive personalized learning decision:

$$\mathbf{Z}_t \rightarrow \mathbf{F}_t \rightarrow \mathbf{H}_t \rightarrow \hat{\mathbf{Y}}_{t+\Delta} \rightarrow \mathbf{R}_t \rightarrow \mathbf{M}_{t+1}, \quad (1)$$

where $\mathbf{Z}_t$ denotes the multimodal observations acquired at time t , $\mathbf{F}_t$ represents the extracted feature vector, $\mathbf{H}_t$ denotes the estimated latent learner state, $\hat{\mathbf{Y}}_{t+\Delta}$ represents the predicted future learning outcome, $\mathbf{R}_t$ denotes the personalized recommendation, and $\mathbf{M}_{t+1}$ represents the updated AI model.

2.8.1. Multimodal wearable sensing model

The learner's real-time information was represented by a multimodal observation vector:

$$\mathbf{Z}_t = [\mathbf{P}_t, \mathbf{B}_t, \mathbf{E}_t, \mathbf{L}_t, \mathbf{C}_t]^T, \quad (2)$$

where $\mathbf{P}_t$ represents physiological measurements, $\mathbf{B}_t$ represents behavioral or movement measurements, $\mathbf{E}_t$ represents engagement-related measurements, $\mathbf{L}_t$ represents learning analytics variables, and $\mathbf{C}_t$ represents contextual information.

The physiological vector may be expressed as

$$\mathbf{P}_t = [HR_t, HRV_t, T_{b,t}, S_t]^T, \quad (3)$$

where HR_t denotes heart rate, HRV_t denotes heart-rate variability, $T_{b,t}$ denotes body or skin temperature, and S_t represents other available physiological indicators.

The behavioral vector can be represented as

$$\mathbf{B}_t = [A_t, M_t, G_t, D_t]^T, \quad (4)$$

where A_t represents physical activity, M_t represents movement intensity, G_t represents gesture or interaction behavior, and D_t represents inactivity or distraction-related information.

Learning analytics were incorporated through

$$\mathbf{L}_t = [Q_t, T_t, C_t, P_t, E_t^a]^T, \quad (5)$$

where Q_t denotes quiz or assessment performance, T_t denotes task completion information, C_t represents content interaction, P_t represents learning progress, and E_t^a denotes historical engagement analytics.

To accommodate measurements obtained at different scales, each continuous feature was normalized using

$$z_{i,t} = \frac{x_{i,t} - \mu_i}{\sigma_i + \epsilon}, \quad (6)$$

where $x_{i,t}$ is the observed value of feature i , μ_i and σ_i are its estimated mean and standard deviation, respectively, and ϵ is a small positive constant introduced to avoid division by zero.

2.8.2. Temporal feature representation

Because learner engagement and physiological responses evolve over time, the current observation alone may not adequately represent the learner's state. A temporal observation window of length K was therefore defined as

$$\mathbf{W}_t = \{\mathbf{F}_{t-K+1}, \mathbf{F}_{t-K+2}, \dots, \mathbf{F}_t\}. \quad (7)$$

The temporal feature representation was obtained through

$$\mathbf{F}_t = \phi(\mathbf{Z}_t), \quad (8)$$

where $\phi(\cdot)$ denotes the feature-extraction and preprocessing function.

A weighted temporal representation can subsequently be expressed as

$$\mathbf{H}_t = \sum_{k=0}^{K-1} \omega_k \mathbf{F}_{t-k}, \quad \sum_{k=0}^{K-1} \omega_k = 1, \quad (9)$$

where ω_k represents the contribution assigned to the observation at lag k . This formulation enables recent and historical observations to contribute differently to learner-state estimation.

2.8.3. Multimodal data fusion

The heterogeneous wearable and learning analytics features were integrated into a unified learner representation. For m sensing modalities, the fused representation can be written as

$$\mathbf{F}_t^* = \sum_{j=1}^m \alpha_{j,t} \mathbf{F}_{j,t}, \quad (10)$$

subject to

$$\alpha_{j,t} \geq 0, \quad \sum_{j=1}^m \alpha_{j,t} = 1, \quad (11)$$

where $\mathbf{F}_{j,t}$ is the feature representation associated with modality j and $\alpha_{j,t}$ is its dynamically estimated contribution.

The modality weights can be obtained using a softmax attention mechanism:

$$\alpha_{j,t} = \frac{\exp(e_{j,t})}{\sum_{r=1}^m \exp(e_{r,t})}, \quad (12)$$

where

$$e_{j,t} = \mathbf{v}^T \tanh(\mathbf{W}_j \mathbf{F}_{j,t} + \mathbf{b}_j). \quad (13)$$

Here, $\mathbf{W}_j$ and $\mathbf{b}_j$ are learnable transformation parameters, and $\mathbf{v}$ is an attention parameter vector. This formulation allows the system to assign greater importance to the information sources that provide stronger evidence about the current learner state.

2.8.4. Latent learner-state estimation

The learner state was modeled as a latent variable incorporating engagement, attention, cognitive readiness, and learning progression:

$$\mathbf{H}_t = [E_t, A_t, C_t, P_t]^T, \quad (14)$$

where E_t denotes engagement, A_t denotes attention, C_t denotes cognitive or learning readiness, and P_t denotes learning progress.

The temporal evolution of the learner state can be formulated as

$$\mathbf{H}_t = f_\theta(\mathbf{H}_{t-1}, \mathbf{F}_t^*, \mathbf{C}_t) + \boldsymbol{\epsilon}_t, \quad (15)$$

where $f_\theta(\cdot)$ represents the learned state-transition function, θ denotes the model parameters, $\mathbf{C}_t$ represents contextual information, and $\boldsymbol{\epsilon}_t$ denotes state-estimation uncertainty.

For a bounded engagement state, the engagement probability can be represented as

$$\hat{E}_t = \sigma(\mathbf{w}_E^T \mathbf{H}_t + b_E), \quad (16)$$

where $\sigma(\cdot)$ is the logistic sigmoid function:

$$\sigma(q) = \frac{1}{1 + \exp(-q)}. \quad (17)$$

Thus, $\hat{E}_t \in [0, 1]$ provides a continuous estimate of the learner's instantaneous engagement state.

2.8.5. Learning-outcome prediction model

The predicted learning outcome was formulated as a function of the current learner state, historical learning information, and contextual variables:

$$\hat{Y}_{t+\Delta} = g_\theta(\mathbf{H}_t, \mathbf{L}_t, \mathbf{S}, \mathbf{C}_t), \quad (18)$$

where $\hat{Y}_{t+\Delta}$ represents the predicted learning outcome over a future interval Δ , $\mathbf{S}$ denotes learner characteristics, and $g_\theta(\cdot)$ represents the trained predictive model.

For a continuous academic performance variable, the prediction may be expressed as

$$\hat{Y}_{t+\Delta} = \mathbf{w}_Y^T \mathbf{H}_t + \mathbf{v}_Y^T \mathbf{L}_t + \mathbf{u}_Y^T \mathbf{C}_t + b_Y. \quad (19)$$

For a binary learning-state classification, the probability of a target state can instead be expressed as

$$P(Y = 1 | \mathbf{H}_t, \mathbf{L}_t, \mathbf{C}_t) = \frac{1}{1 + \exp[-(\mathbf{w}^T \mathbf{H}_t + \mathbf{v}^T \mathbf{L}_t + \mathbf{u}^T \mathbf{C}_t + b)]}. \quad (20)$$

The predictive model was trained by minimizing a regularized objective function:

$$\mathcal{L}(\theta) = \frac{1}{N} \sum_{i=1}^N l(Y_i, \hat{Y}_i) + \lambda \|\theta\|_2^2, \quad (21)$$

where $l(\cdot)$ denotes the prediction loss, N is the number of observations, λ is the regularization coefficient, and $\|\theta\|_2^2$ controls model complexity.

2.8.6. Personalized recommendation model

Personalized learning recommendations were generated by mapping the estimated learner state to a set of candidate instructional actions:

$$\mathbf{R}_t = \pi_{\theta}(\mathbf{H}_t, \hat{\mathbf{Y}}_{t+\Delta}, \mathbf{S}, \mathbf{C}_t), \quad (22)$$

where $\pi_{\theta}(\cdot)$ denotes the recommendation policy.

Let $\mathbf{A}$ represent the set of available instructional actions, such as content revision, additional practice, difficulty adjustment, rest interval, multimedia presentation, or instructor intervention. The optimal recommendation can then be formulated as

$$\mathbf{R}_t^* = \operatorname{argmax}_{r \in \mathbf{A}} U(r | \mathbf{H}_t, \hat{\mathbf{Y}}_{t+\Delta}, \mathbf{S}, \mathbf{C}_t), \quad (23)$$

where $U(\cdot)$ represents the expected utility of recommendation r .

A multi-objective recommendation utility can be expressed as

$$U(r) = \lambda_1 G(r) + \lambda_2 E(r) + \lambda_3 P(r) - \lambda_4 L(r) - \lambda_5 C(r), \quad (24)$$

where $G(r)$ represents expected learning gain, $E(r)$ represents expected engagement, $P(r)$ represents personalization quality, $L(r)$ represents cognitive or interaction load, and $C(r)$ represents computational or resource cost. The coefficients $\lambda_1, \dots, \lambda_5$ determine the relative importance of the respective objectives.

2.8.7. Real-time adaptive updating

The proposed system was designed to continuously incorporate new learner observations. Let θ_t denote the AI-model parameters at time t . The model parameters can be updated using a gradient-based rule:

$$\theta_{t+1} = \theta_t - \eta \nabla_{\theta} L_t(\theta_t), \quad (25)$$

where η represents the learning rate and $\nabla_{\theta} L_t$ is the gradient of the current loss function with respect to the model parameters.

To reduce abrupt changes caused by individual observations, an exponentially weighted update can also be represented as

$$\theta_{t+1} = (1 - \alpha)\theta_t + \alpha\theta_t^{\text{new}}, \quad 0 < \alpha < 1, \quad (26)$$

where θ_t^{new} denotes the parameters estimated from newly acquired learner information and α controls the adaptation rate.

The complete adaptive learning process can therefore be represented as

$$\mathbf{Z}_t \rightarrow \mathbf{F}_t \rightarrow \mathbf{F}_t^* \rightarrow \mathbf{H}_t \rightarrow \hat{\mathbf{Y}}_{t+\Delta} \rightarrow \mathbf{R}_t^* \rightarrow \theta_{t+1}. \quad (27)$$

This closed-loop formulation enables the system to continuously sense learner information, estimate the learner's current state, predict subsequent learning performance, select an appropriate instructional intervention, and update the underlying AI model using newly acquired evidence.

2.8.8. Model evaluation criteria

The mathematical model was tested by utilizing a combination of prediction, classification, and individualization metrics. For the prediction of continuous learning outcomes, the MAE is defined as

$$MAE = \frac{1}{N} \sum_{i=1}^N |Y_i - \hat{Y}_i|, \quad (28)$$

while the RMSE was calculated as

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (Y_i - \hat{Y}_i)^2}. \quad (29)$$

The coefficient of determination was calculated as

$$R^2 = 1 - \frac{\sum_{i=1}^N (Y_i - \hat{Y}_i)^2}{\sum_{i=1}^N (Y_i - \bar{Y})^2}. \quad (30)$$

For binary learner-state classification, precision, recall, and the F1-score were defined, respectively, as

$$Precision = \frac{TP}{TP + FP}, \quad (31)$$

$$Recall = \frac{TP}{TP + FN}, \quad (32)$$

and

$$F1 = 2 \frac{Precision \times Recall}{Precision + Recall}. \quad (33)$$

where TP , FP , and FN denote true-positive, false-positive, and false-negative classifications, respectively.

The personalization performance can additionally be quantified using recommendation utility:

$$PU = \frac{1}{N} \sum_{i=1}^N U(R_i), \quad (34)$$

where PU represents the mean personalization utility across learners.

Finally, the computational responsiveness of the real-time system can be represented by

$$T_{\text{total}} = T_{\text{sense}} + T_{\text{pre}} + T_{\text{infer}} + T_{\text{rec}}, \quad (35)$$

where T_{sense} is the sensing/acquisition time, T_{pre} is the preprocessing time, T_{infer} is the AI inference time, and T_{rec} is the recommendation-generation time. A lower T_{total} indicates greater suitability for real-time personalized learning applications.

2.9. Mixed-methods integration, triangulation, and interpretive limitations

Integration occurred at the level of interpretation in light of the sequential explanatory mixed methods research design. The quantitative results offered statistical support regarding the connection between wearable learning experience, real-time engagement, learning analytics, SCI, EEP, and academic performance. In the next step, the qualitative results helped explain the participants' experiences with regard to the stated connections.

Triangulation was used to compare evidence obtained from different sources and to examine convergence and divergence of the numeric findings and participant reports. Such integration made it possible to get a more comprehensive interpretation of the role of the AI-enabled wearable learning system in personalized and student-centered education.

The integration of interpretation was limited by the design of the study in terms of its capability to provide evidence that the observed changes in pre-test and post-test scores were the result of the impact of the AI-enabled wearable learning system. In particular, a growth in the test scores cannot be seen as definitive evidence of that influence since there was no control group for comparison included in the study.

2.10. Validity, reliability, and measurement quality

The validity and reliability of the instruments used in the research were established prior to the statistical analysis and interpretation of the measurement model. The content validity of the measurement model was established by expert assessment of questionnaire items and study variables in regard to their relevance, clarity, comprehensiveness, and appropriateness. The expert assessment included specialists in such areas as AI, educational technology, wearable computing, instructional design, learning analytics, and educational measurement.

The construct validity of the measurement model was assessed using the PLS-SEM measurement model. The reliability of indicators for reflective constructs was measured by standardized outer loadings, while the convergent validity was assessed by the AVE. If the AVE is equal to or exceeds 0.50, then it indicates that the construct explains at least half of the variance in the indicators, and it can be considered valid for convergent validity [9]. Internal consistency reliability was assessed by Cronbach's alpha and CR, and it is recommended to have a value of about 0.70 or higher as acceptable reliability for established measurement models [9]. It should be noted that the recent methodological advice is to report several reliability measures instead of reporting only one Cronbach's alpha measure.

The discriminant validity of the constructs was assessed by the HTMT ratio. The HTMT criterion was developed specifically for assessing discriminant validity in variance-based structural equation modeling, and it was found to have advantages compared to traditional approaches under several conditions [11, 20]. An HTMT value less than 0.85 can be considered a conservative criterion when constructs are conceptually distinct, while 0.90 might be applicable when constructs are conceptually similar [9, 21]. The multicollinearity of the constructs and indicators was checked using the VIF to make sure that the collinearity does not affect the estimation of the model [9].

These statistics of reliability and validity are reported in the Results section by such measures as indicator loading, Cronbach's alpha, CR, AVE, HTMT, and VIF. Thus, instead of reporting the assumptions or theoretical description of the methodological procedures, empirical evidence of the adequacy of the measurement model is provided [9, 11].

Also, in order to improve the consistency and measurement reliability of the physiological, behavioral, and engagement variables collected by the wearable sensing system, the process of device calibration and repeated measurements was performed before and during the data collection procedure.

2.11. Ethics and participant protection

Since the study employed human participants and involved collection of physiological, behavioral, academic, and questionnaire data, ethical clearance was sought prior to the collection of data. The manuscript should clearly state the name of the ethics committee/board that granted the clearance and should state the official approval number: PGD/EEE/2019/002.

All of the participants were informed regarding the objectives and procedures of the experiment prior to their enrollment in the experiment. Each individual voluntarily chose to be a part of the experiment and was made aware that he or she could withdraw without penalty at any point during the experiment.

As physical and behavioral data were collected using wearable sensing technologies, there were other measures in place to ensure confidentiality of the participants. The identities of the

participants were either coded or anonymized before analysis, and only selected members of the research team had access to the datasets.

Use of physiological and behavioral data was restricted to the uses defined in the study. The AI system used was seen as an educational decision-making tool and not as a replacement for the expertise of the educational professionals. Special care was taken on the issues of fairness, transparency, data minimization, privacy, and inequalities in wearable and Internet technology access.

2.12. Integrating quantitative and qualitative findings

Integrating the quantitative and qualitative findings took place during the interpretive phase of the sequential explanatory design. The quantitative phase produced statistical patterns and relationships related to wearables, learning analytics, learner engagement, personalized learning, instructional innovation, and achievement. The qualitative stage provided contextual interpretations of the results based on the perspectives of both the teacher and the learner.

Triangulation was used in investigating convergence, complementarity, and divergence between the quantitative and qualitative data. Findings from the quantitative results that needed further interpretation were contrasted against the corresponding qualitative themes, while those from the qualitative results that went beyond the statistical results were seen as contextual results and not verification of the statistical results.

Such an integration of the findings led to a complete interpretation of the potential contribution of AI-powered smart wearable learning systems to personalized and student-centered education. Yet, the mixed methods approach to integration was used to enhance the interpretation and contextualization and not to prove causation.

2.13. Data management and availability

Empirical data have been collected through the use of questionnaires, pre-test and post-test evaluation, wearables, learning analytics, interviews, and focus group discussions. In this case, the above statement on no new data being collected or analyzed is irrelevant and hence has been deleted.

As the dataset consists of participant-based physiological, behavioral, academic, and survey data, the unrestricted public availability may pose potential privacy issues. Hence, the actual access to the data must be described in the Data Availability Statement approved under the ethics of the study. De-identified data and analysis materials may be deposited in an appropriate repository if necessary or, alternatively, the authors of the research may be contacted by interested researchers.

2.14. Research hypotheses

The hypotheses that are used to guide the quantitative research are:

H1: There exists a significant positive correlation between an AI-based wearable learning experience and academic performance.

H2: There exists a significant positive correlation between learning engagement and academic performance.

H3: There exists a significant positive correlation between learning analytics performance and academic performance.

H4: There exists a significant positive correlation between innovation for students and academic performance.

These hypotheses concern correlations between the variables as examined using the structural model through PLS-SEM.

2.15. Ethical considerations

Ethical principles were observed in all phases of the research to ensure the rights, privacy, confidentiality, and well-being of the participants. This research was performed in the Department of Electrical and Electronics Engineering, FUOYE. Participants were made aware of the aim of the research, its process, and how the data obtained would be used. Participation was on a voluntary basis, and informed consent was obtained, which allowed the participants to withdraw from the research process at any stage without facing any penalties. The data collected in the research were only that required by the research objectives and were kept anonymous or pseudonymous when needed. Access to research data was controlled to authorized people and stored in a secure place. AI-enabled outputs were used only for decision support purposes.

3. Results and Discussion

3.1. Characteristics of participants

In this study, 344 participants were recruited from two Federal universities in the southwestern part of Nigeria. These included 320 PhD students and 24 instructors. The PhD students formed 93.0% of the total number of participants, whereas instructors formed 7.0% of the total. The mean age of participants is 30 years for PhD students and 40 years for instructors,

respectively. All subjects in the study are female. The simple random sampling method was used to select the subjects so that each participant would have an equal opportunity to be selected. The experiment was conducted over a span of six months during which 320 PhD students were involved.

The demographic and sampling details of the study subjects are given in Table 3.

The inclusion criteria used for the learners included their active participation in the doctoral program in one of the participating institutions, being able to stay available throughout the six-month research period, being involved in the learning process using the AI-enabled smart wearable, as well as taking part in the pre-test and post-test. Instructors were selected based on their active involvement in the teaching process in the participating learning environment.

3.2. Descriptive statistics of the study variables

Descriptive statistics of the main research variables are shown in Table 4. Some of the variables studied in the current research are AI-Enabled Wearable Learning Experience (AWLE), Real-Time Learning Engagement (RTLE), Learning Analytics Effectiveness (LAE), Student-Centered Innovation (SCI), Educational Equity Perception (EEP), and Academic Achievement (AA). Table 2 shows the descriptive statistics for the key constructs of this study. From the above findings, it is evident that there are positive perceptions of the AI-based smart wearable learning environment.

The results indicate fairly positive attitudes toward the use of the AI-integrated smart wearable learning environment. The mean scores for AWLE ($M = 4.28$, $SD = 0.58$), SCI ($M = 4.19$, $SD = 0.60$), RTLE ($M = 4.16$, $SD = 0.61$), and LAE ($M = 4.11$, $SD = 0.56$) were higher than those for EEP ($M = 3.97$, $SD = 0.69$).

Table 3
Participants and sampling characteristics

Characteristic	Learners	Instructors
Number of participants	320	24
Percentage of total sample	93.0%	7.0%
Age	30 years	40 years
Gender	Female	Female
Participant role	PhD learner	Instructor
Participating institutions	FUOYE and FUTA	FUOYE and FUTA
Number of institutions	2	2
Sampling method	Simple random sampling	Simple random sampling
Study duration	6 months	6 months
Completed pre-test and post-test	320	Not applicable
Total sample	344	—

Table 4
Descriptive statistics of the study variables

Variable	N	Mean	SD	Interpretation
AI-Enabled Wearable Learning Experience (AWLE)	320	4.28	0.58	High
Real-Time Learning Engagement (RTLE)	320	4.16	0.61	High
Learning Analytics Effectiveness (LAE)	320	4.11	0.56	High
Student-Centered Innovation (SCI)	320	4.19	0.60	High
Educational Equity Perception (EEP)	320	3.97	0.69	Moderate-High
Academic Achievement – Post-Test	320	78.60	8.70	Improved

Even though EEP showed the lowest result, it was still relatively high.

What is worth mentioning about the relatively low EEP score is that technological effectiveness does not ensure equal access to the technology used. Learners' financial ability to buy devices, availability of electricity, internet connection, digital literacy, technical assistance, and various other social and economic aspects can influence the degree to which learners use the technologies equally.

3.3. Pre-test and post-test academic achievement

All 320 learners took both the pre-test and post-test, thus making it possible to evaluate the academic performance in a paired fashion. In accordance with the methodology, the pre-test and post-test scores have been considered as paired observations due to the fact that the same set of participants has taken both tests. Table 5 shows the comparison of the learners' academic performance both before and after the intervention. From the results, there is an improvement in the learners' the post-test mean was higher than the pre-test mean.

The mean score was 62.40 at pre-test and 78.60 at post-test ($SD = 8.70$), reflecting a descriptive change of 16.20. The reduction in standard deviation from 9.80 to 8.70 suggests that there is a small decrease in the spread of post-test scores.

Since the participants performed both tests, a paired-samples test is suitable. Nevertheless, the exact t -statistic, degrees of freedom, significance level, confidence intervals, and effect size cannot be computed using just the descriptive statistics provided since neither the standard deviation of the difference in paired variables nor individual paired samples is known. Consequently, such statistics need to be derived from SPSS paired-samples test output before submission.

This development should not be taken as definite proof of the effect of the intervention since there is no randomized control group. The approach acknowledges this limitation.

3.4. Correlation analysis

The correlation analysis technique by Pearson was used to investigate the relationships among the core constructs of this research. It can be noted that there are positive correlations

between AWLE, RTLE, LAE, SCI, and EEP. The Pearson correlation coefficients of the main constructs are represented in Table 6. In accordance with the findings of this study, there were positive correlations between AI-based wearable learning experience, learning engagement, learning analytics, SCI, and education equity.

The obtained results showed positive correlations between the key constructs of the learning systems framework. According to the results, the strongest correlation was observed between SCI and AA ($r = 0.79$), followed by LAE and AA ($r = 0.76$), RTLE and AA ($r = 0.74$), and AWLE and AA ($r = 0.72$).

The results also demonstrated significant correlations between the independent variables. Namely, there was a positive correlation between AWLE and SCI ($r = 0.77$), RTLE and LAE ($r = 0.76$), and LAE and SCI ($r = 0.75$). Thus, the results show that the dimensions of AI-based wearable learning are connected to each other and cannot be considered independent elements.

EEP had moderate correlations with other constructs, with values varying between $r = 0.58$ and $r = 0.63$. This means that the quality of the learning experience and educational equity are interrelated but may also be affected by other factors.

The correlation between EEP and AA was not identified based on the provided empirical results and, thus, cannot be estimated.

3.5. Structural model and hypotheses testing

A total of four hypotheses were posited in the methodology section. Hypothesis H1 states there is a correlation between AI-based wearable learning experience and academic achievement; Hypothesis H2 states there is a correlation between learning engagement and academic achievement; Hypothesis H3 states there is a correlation between learning analytics performance and academic achievement; and Hypothesis H4 states there is a correlation between SCI and academic achievement. The findings of the structural model analysis and hypothesis testing are summarized in Table 7. It can be observed that there are statistically significant correlations between all four proposed variables and academic achievement.

PLS-SEM analyses revealed that there exist statistically significant positive associations between all four hypothesized observed associations and AA. SCI had the largest standardized path coefficient ($\beta = 0.38$, $t = 6.05$, $p < 0.001$), which shows that SCI was the most influential predictor out of the four hypothesized relationships.

The strongest observed association is LAE ($\beta = 0.34$, $t = 5.38$, $p < 0.001$), followed by AWLE ($\beta = 0.29$, $t = 4.68$, $p < 0.001$) and RTLE ($\beta = 0.26$, $t = 4.17$, $p < 0.001$). The results indicate that the role of AI wearables in education can be improved with

Table 5
Pre-test and post-test academic achievement

Assessment	N	Mean	SD	Mean difference
Pre-test	320	62.40	9.80	—
Post-test	320	78.60	8.70	16.20

Table 6
Pearson correlation matrix

Variable	AWLE	RTLE	LAE	SCI	EEP	AA
AWLE	1.00	0.74	0.71	0.77	0.60	0.72
RTLE	0.74	1.00	0.76	0.72	0.58	0.74
LAE	0.71	0.76	1.00	0.75	0.63	0.76
SCI	0.77	0.72	0.75	1.00	0.61	0.79
EEP	0.60	0.58	0.63	0.61	1.00	Not reported
AA	0.72	0.74	0.76	0.79	Not reported	1.00

Table 7
PLS-SEM structural path coefficients and hypothesis testing

Hypothesis	Path relationship	β	<i>t</i> -value	p-value	Decision
H1	AWLE $\rightarrow$ AA	0.29	4.68	<0.001	Supported
H2	RTLE $\rightarrow$ AA	0.26	4.17	<0.001	Supported
H3	LAE $\rightarrow$ AA	0.34	5.38	<0.001	Supported
H4	SCI $\rightarrow$ AA	0.38	6.05	<0.001	Supported

a combination of the data obtained by wearables with learner-centered instruction and feedback.

3.6. Learning analytics and real-time sensing indicators

Findings on behavioral performance, learning analytics, and wearables are provided in Table 8. It can be seen from the results that engagement, completion, feedback, and recommendation acceptance are extremely high.

These findings demonstrate active involvement in the AI-based learning environment. The average time spent by the learners in the learning environment is 50.8 minutes per day, with an average completion rate of 86.5% for the modules and 79.4% usage of AI-generated feedback. Personalized suggestions were agreed to by 81.7% of the learners, with an average engagement score of 87.3%.

An accuracy rate of 96.2% for the wearable sensors suggests that there is high performance of measurements. But the final paper must specify the reference measure, the method of validation, sample size, and the accuracy measure employed in obtaining this figure. The research methodology shows that wearable sensors were calibrated before and during data gathering.

3.7. Validation of the proposed AI-enabled smart wearable learning system

In order to test the validity of the developed AI-based smart wearable learning system framework, different kinds of validations have been carried out, including testing the measurement model, testing the structural model, finding the most reliable measure, and qualitative validation. In the multivariate validation process, the framework's reliability, validity, predictive power, and application to education are guaranteed. This is because of the multidimensional nature of the phenomenon under study, such as learner engagement and performance in e-learning.

3.7.1. Measurement-model validation

Model measurement validation was carried out using indicator reliability, Cronbach's alpha, CR, AVE, and HTMT ratio. The reliability of the measures was determined by Cronbach's alpha and CR, and AVE helped establish convergent validity. In general, all these measurements have been performed under the PLS-SEM approach to evaluate the quality of latent variable measurement [9]. Constructs that passed the reliability and convergent validity tests were included in the structural model estimation.

Construct discriminant validity was evaluated based on the HTMT criterion. This step is especially important for constructs like AWLE, learning engagement, learning analytics, and SCI, as these constructs belong to the group of theoretically related constructs. Construct validation helps avoid wrong conclusions drawn because of measuring the same variable by two indicators [9].

3.7.2. Validation of the structural model

Upon confirmation of the measurement model, the structural model was validated on the basis of path coefficients (β), bootstrapped *t*-values, and significance levels. The structural model confirmed the validation of the hypothesized relationships between AI-based wearable learning experience, RTLE, LAE, SCI, and academic success. All four paths showed positive and significant relationships in the analysis. It is worth noting that SCI showed the highest significant relationship with academic success ($\beta = 0.38$, $t = 6.05$, $p < 0.001$). Other significant paths included LAE ($\beta = 0.34$, $t = 5.38$, $p < 0.001$), AI-based wearable learning experience ($\beta = 0.29$, $t = 4.68$, $p < 0.001$), and RTLE ($\beta = 0.26$, $t = 4.17$, $p < 0.001$). These results support previous research indicating that educational technology impacts learning engagement combined with teaching and learning-centered approaches [2, 11, 13].

3.7.3. Machine learning model performance evaluation

Machine learning algorithm was assessed using the following algorithms: RF, SVM, ANN, and LSTM. The evaluation of the models was conducted using such metrics as accuracy, precision, recall, F1 score, confusion matrices, AUC-ROC, MAE, and

Table 8
Learning analytics and behavioral performance indicators

Indicator	Mean value	Interpretation
Learning time (minutes/day)	50.8	High engagement
Module completion rate (%)	86.5	High completion
AI feedback utilization (%)	79.4	Strong utilization
Daily interaction frequency	39.6	High activity
Average engagement score	87.3%	Highly engaged
Personalized recommendation acceptance (%)	81.7	High acceptance
Wearable sensor data accuracy (%)	96.2	Excellent

RMSE. The use of complementary statistical metrics is essential since accuracy alone can give an incomplete picture of the performance of the model especially in cases when different learner states or outcome categories are unevenly represented. Thus, it is necessary to use various dimensions when testing the robustness of statistical models [15].

The statistical models have been built in order to distinguish between the different learner states and provide personalized interventions using the analysis of physiological, behavioral, and learning analytics data. It conforms to the general tendency toward the development of intelligent educational systems that use learner data in order to provide adaptive feedback and support instructional decisions [16, 21]. However, it is vital to present the actual performance indicators of the RF, SVM, ANN, and LSTM models. Whereas the methodological information provides insights into the measures used in the assessment procedure, they lack the empirical data needed for their calculation.

3.7.4. Academic performance validation

Academic performance was further investigated in the context of a pre-test/post-test comparison where the mean academic achievement score was associated with higher values from 62.40 (SD = 9.80) in the pre-test period to 78.60 (SD = 8.70) in the post-test period—an average improvement of 16.20 points. Such a result constitutes tentative evidence that suggests the effectiveness of the proposed learning environment in improving learner performance. AI-assisted learning has similarly been shown to potentially improve learning outcomes, motivation, and self-regulated learning under the conditions of proper integration into the instructional process [21].

Nonetheless, the observed association with higher values of scores needs to be taken with caution since, without the presence of an additional randomized control group, it is impossible to conclude about the existence of the direct causation between the proposed wearable learning intervention and academic achievement. Educational results may also be affected by instructional quality, learner characteristics, prior knowledge, motivation, and other contextual factors [1, 7]. In this way, the current finding can only be regarded as evidence of the observed improvement rather than experimental proof of causation.

3.7.5. Qualitative validation

Qualitative validation was performed using focus groups with learners as well as interviews with educators in order to acquire contextual information with regard to the usability, acceptability, educational merit, and implementation challenges of the proposed solution. Qualitative analysis covered a wide range of topics including personalization, real-time sensing, learning analytics, learner engagement, usability, technology adoption, instructional innovation, privacy, ethics, and implementation challenges. Such kind of validation complements the quantitative validation by allowing an understanding of the opinions of the learners and instructors about the practical aspects of implementation of the discussed AI-assisted education technology. Such issues were already stressed in previous research [3, 5].

The qualitative validity aspect is especially important to verify the concept of learner-centeredness since the technical validity alone does not ensure that an educational-pedagogical validation of the model is provided. The main elements of the technology-mediated learning are learner involvement, the teacher's role, instructional strategies, and characteristics of learning activities [2, 13]. Therefore, the combination of both quantitative and qualitative dimensions will be important in analyzing the proposed model.

3.7.6. Ethical and responsible-AI validation

The proposed framework was also assessed from the viewpoint of ethical implications related to the processing of physiological, behavioral, engagement, and learning-related data. AI-based educational solutions need security mechanisms regarding privacy, transparency, fairness, accountability, informed consent, and responsible governance of data [10, 16]. This problem acquires special importance in the case of wearable learning technologies as physiology-related data can be more private than ordinary educational data. In this respect, the suggested framework embraces the issues of data management, access control, privacy of learners' information, and data ethics.

Also, the issue of ethics is related to educational equality. Even though there is potential for the use of AI technologies and wearables to provide personalized education, unequal access to basic equipment, Internet access, electrical power, digital skills, and technical assistance can be among the causes of educational inequality. As seen in previous studies, technology implementation should take into account a wider context of the society where this innovation appears [17, 19].

3.7.7. Overall validation outcome

Thus, as seen from the findings of the validation process, convergent evidence from the quantitative, statistical, and qualitative angles regarding the feasibility of the suggested AI-based smart wearable learning framework can be found. The positive descriptive findings, the higher value of 16.20 points for academic achievement, statistically significant relationships identified by PLS-SEM analysis, and the qualitative validation approach indicate the possibility of offering a personalized and adaptive, learner-centered, and data-driven learning. These results coincide with those stated in the existing literature about the potential offered by educational technologies [2, 6, 11].

3.8. Discussion

Overall, positive attitudes toward the smart wearable learning environment driven by AI were observed, with mean scores being quite high (AWLE, $M = 4.28$; SCI, $M = 4.19$; RTLE, $M = 4.16$; and LAE, $M = 4.11$). An improvement in academic results was seen—from 62.40 to 78.60, which is equal to a 16.20-point of higher values; still, it is impossible to speak about a causal relationship due to the lack of a randomized control group. The most significant correlation with achievement was demonstrated by SCI ($r = 0.79$), followed by LAE ($r = 0.76$), RTLE ($r = 0.74$), and AWLE ($r = 0.72$). Moreover, PLS-SEM identified significant paths for SCI ($\beta = 0.38$), LAE ($\beta = 0.34$), AWLE ($\beta = 0.29$), and RTLE ($\beta = 0.26$; $p < 0.001$). System use measurements reflected active use as well. However, it is necessary to pay attention to this.

3.9. Limitations and future research

There are a number of limitations associated with the study. First, the use of measures that are questionnaire-based could be susceptible to self-reporting and social desirability biases. Even if the wearable sensors were accurate enough with an accuracy of 96.2%, measurement errors could result from calibration, sensor noise, and individual variation. The lack of a randomized control group is another limitation to the study as any changes in the learning outcomes may be caused by instructional, temporal, or learner-related aspects. The study was carried out in two Federal universities in Southwestern Nigeria and cannot therefore be generalized to other educational levels, institutions, geographical

locations, and countries. Financial constraints, infrastructure needs, technical support, and connectivity issues, among others, can pose obstacles to the wide-scale implementation of the study. Ethical issues relating to physiological and behavioral data need to be handled carefully.

4. Conclusions

Based on the results of the current research, it is possible to speak about empirical evidence that the combination of the elements of AI, wearables, learning analytics, and pedagogy can help in the development of an intelligent learning ecosystem contributing to the improvement of the quality of personalized learning, engagement, performance, and instruction. The proposed AI-enabled wearable learning framework allows speaking about the possibility of the implementation of wearable computing, the Internet of Things, machine learning, and data-driven learning in practice to facilitate the process of real-time monitoring of learners' activities, feedback provision, and learner-oriented learning. It could be argued that appropriate use of learning analytics and intelligent personalization has the ability to greatly improve both learning and teaching processes. Implementation of such solutions comes with a variety of challenges, such as privacy, digital literacy, technological infrastructure, cost, and organizational readiness. This research will contribute to the development of Artificial Intelligence in Education. In the future, emphasis should be put on privacy-preserving AI, generative AI-based personalization, and longitudinal evaluation of intelligent learning ecosystems.

Recommendations

Learning organizations need to make sure that the investments are geared toward intelligent wearable devices for learning through AI, creation of strong digital infrastructure, teacher training on AI and learning analytics, and ethical use of the data. Equity of opportunities needs to be taken into consideration when it comes to the use of wearables and the internet.

Ethical Statement

This study was reviewed by the FUOYE, and formal ethical approval was not required in accordance with the institution's regulations.

Conflicts of Interest

The author declares that he has no conflicts of interest to this work.

Data Availability Statement

Data are available from the corresponding author upon reasonable request.

Author Contribution Statement

Olarewaju Peter Ayekoribe: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration.

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