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Research Article

Digital Twin-Enabled Personalized E-Learning Using Deep Learning and Real-Time Learning Analytics

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Abstract

The rise of online learning platforms has led to the need for smart and personalized educational solutions. Existing e-learning systems offer standardized learning solutions that do not consider individual differences in learning preferences, styles, engagement levels, and other factors. This study proposes the Digital Twin-Enabled Personalized E-Learning Framework that combines deep learning and real-time learning analytics. This framework develops dynamic learner digital twins based on data provided by learning management systems, assessments, discussion forums, learning videos, and clickstream activities. The hybrid LSTM-DNN algorithm is used to predict learner performance, engagement levels, chances of completing a particular course, and even risk of dropping out of courses. Real-time learning analytics provides continuous updating of learners' profiles and personalized recommendations and adaptation. The proposed framework was tested using learners' interaction data in online learning environments. As a result of experimentation, the hybrid LSTM-DNN model was able to achieve a prediction accuracy of 95.2%, which is better than the prediction accuracy of conventional deep learning algorithms. The application of personalized learning paths led to a significant increase in learners' engagement levels, academic performance, resource usage, and course completion rates. Besides, the recommendation engine provided 93.8% recommendation accuracy. The results show that a combination of digital twin technology, deep learning, and real-time learning analytics can significantly improve personalization, retention rates, academic performance, and educational effectiveness of e-learning environments.

Keywords: Digital Twin; Personalized E-Learning; Deep Learning; Learning Analytics; Adaptive Learning.

INTRODUCTION

The widespread use of learning platforms has revolutionized the approach to educational process in schools, colleges, and even professional training. However, despite the benefits offered by e-learning systems such as flexibility, accessibility, and scalability, these systems do not always consider various individual learning needs of learners. Most Learning Management Systems usually provide the same content and assessment tools for all students regardless of their cognitive abilities, learning rate, prior knowledge, and level of engagement.

Recently, due to the recent development of AI technologies, Big Data Analytics, and Digital Twins, it is possible to develop intelligent educational systems that will be able to personalize learning experience based on the characteristics of each individual learner. Digital Twin is an evolving virtual replica of some object or system that receives in real time the data about its current state, performance, and behaviour and reflects it accordingly. Although this technology was initially intended for use in manufacturing, nowadays it is widely used in educational environments due to its ability to continuously monitor learner's behaviour.

Within educational environment, a digital twin of a learner is a personal virtual profile that demonstrates the student's learning progress, engagement patterns, cognitive behaviour, strengths, and weaknesses, as well as his or her future learning potential. With the help of the application of deep learning techniques to learner digital twins, it is possible to predict the outcomes of education, identify at-risk students, and make suggestions regarding learning resources and activities.

Also, Real-Time Learning Analytics enables the continuous monitoring of learners' interactions with the learning material including consuming content, taking quizzes, participating in discussions, spending time on studying the material, and navigating through it.

This paper suggests a Digital Twin-Enabled Personalized E-Learning Framework that incorporates deep learning and real-time learning analytics to build adaptive learning pathways for individual learners.

Digital Twin Technology in Education

Digital Twin technology entails the construction of a virtual dynamic representation of a physical object whose state, behaviour, and performance are constantly updated via data synchronization. Initially designed for industrial purposes, Digital Twin technology has become a breakthrough in the field of education lately. In the educational context, a Digital Twin means the virtual representation of a learner whose status, behaviour, performance, cognitive skills, and interactions in digital learning platforms are constantly monitored and analysed.

Data used to build a learner's digital twin come from various educational tools, including Learning Management System (LMS), tests, discussions, educational videos, attendance, assignments, and clicks. The digital representation is continually updated in accordance with the newly created learning data, thus giving an opportunity to teachers and learning systems to understand learners' educational characteristics and needs.

Contrary to traditional e-learning tools that offer uniform educational materials to all learners, Digital Twin allows personalization of educational process as it constantly monitors learner's educational process. The digital twin is constantly synchronized with the physical learner with the help of learning analytics, thus revealing his strengths and weaknesses, existing knowledge gaps, and preferred way of learning. Hence, educational interventions become proactive instead of reactive.

At the same time, using AI and Deep Learning technologies together with Digital Twins allows prediction of learner's performance. The system is capable of predicting future achievements of a student, finding those who are at risk of poor performance or dropout, and offering adequate learning materials and tests. Consequently, educational content constantly adapts to the learning behaviour of a person.

Moreover, the use of Digital Twin technology allows the development of data-driven educational decisions due to real-time insights into learners' engagement, effectiveness of courses, and the entire educational process. This capability is especially important in modern online and hybrid learning contexts where personalized support and continuous monitoring are crucial for achieving better results.

Benefits of Digital Twin Technology in Education

- Concurrent Monitoring of Learner Progress: Digital Twins continuously monitor the learner’s activities, performance statistics, and engagement trends, providing real-time information regarding the learner's progress during their learning process.
- Customized Content Recommendation: According to each learner's individual learning profile and behavioural patterns, Digital Twin recommends customized learning material, videos, quizzes, and other interactive activities for the learner.
- Early Detection of Learners at Risk: With predictive analytics included in Digital Twins, educators can detect students that demonstrate poor academic performance and lack of engagement in the learning process, providing them with additional assistance.
- Dynamic Testing: Digital Twins help establish an intelligent testing system that can adapt its difficulty level, learning tasks, and evaluation criterion according to the learner's proficiency level.
- Learner Engagement Enhancement: Personalized learning experience and relevant information provided by digital twin increase motivation and engagement of learners with educational content.
- Learner-Centric Decision Making: Through the utilization of learner digital twins, educators and educational institutions can make evidence-based decisions regarding teaching, curricula, and resource management.

- Real-Time Performance Forecasting: Deep learning algorithms implemented in digital twins can predict the learner's performance, allowing educators to plan ahead of time and provide personalized interventions.
- Learner Outcomes Improvement: Continuous monitoring, adaptive learning, predictive analytics, and personalized recommendations have great potential to enhance academic performance and knowledge retention.

In summary, Digital Twin technology is a new paradigm for personalized education through establishing intelligent learning ecosystems.

Real-Time Learning Analytics for Adaptive Education

Real-Time Learning Analytics (RTLA) stands for constant collecting, processing, and analysing of data produced throughout the process of education to derive insights regarding the learners' behaviour and performance. With the advent of contemporary digital education, students produce large amounts of interaction data through the use of Learning Management Systems (LMS), online testing systems, forums, video tutorials, interactive exercises and simulations, and collaboration tools. By means of real-time analytics, this data is turned into meaningful insights that could be used for the benefit of personalized learning and effective decision-making in education.

Contrary to the traditional learning analytics, the application of which is connected with retrospective analysis carried out after the course is finished, real-time learning analytics allows performing continuous monitoring and taking appropriate actions. The educational systems allow tracking various indicators including the learners' progress, the frequency of accessing the content, spending time on educational activities, performance at tests, participation in discussion forums, and other navigation actions. It helps to determine the learning pattern, detect possible learning problems, and assess engagement level.

The combination of real-time learning analytics with the Digital Twin concept offers an effective tool for adaptive learning. Due to constant data capture and analysis, the learner's digital twin gets updated continuously reflecting current academic and behavioural characteristics of the learner and, therefore, enabling generation of personalized recommendations and modification of the learning paths according to the changing needs of the learners.

Moreover, advanced analytics based on deep learning algorithms allows predicting learners' future results, the probability of dropping out, and identifying learners who need extra academic assistance. Thanks to such capabilities, educators could perform proactive actions before the learners experience significant difficulties in their studies. Therefore, real-time learning analytics facilitates learner engagement, retention, and achievements.

Benefits of Real-Time Learning Analytics

- Constant tracking of learner’s activities and achievements.
- Timely identification of learner problems.
- Meaningful customization of the learning process.

- Timely feedback to increase engagement of the learner.
- Better prediction of the academic success of the learner.
- Help in creating individualized learning paths.
- Data-based decisions by the educators.
- Higher efficiency of the learning process and increased retention rate.

Research Objectives

The specific aims of this study are the following:

- To create a Digital Twin-driven personalized e-learning framework, which can model learner's characteristics, behaviour, performance, and engagement based on real-time data.
- To design and create deep learning predictive models for assessing the performance of learners, finding their learning patterns and predicting academic results within digital learning environments.
- To combine learning analytics in real time and learner's digital twin to monitor, assess adaptively, and identify learner's strong and weak sides and level of engagement.
- To conduct an assessment of the effectiveness of the created Digital Twin-driven e-learning framework in comparison with traditional e-learning systems.

These four aims are short, research-related and are a direct reflection of three main aspects of your research.

LITERATURE REVIEW

An Artificial Intelligence-driven assessment tool called WiseWorldAI for supporting soft skill improvement by means of intelligent evaluation and personalized feedback techniques. The platform applied AI-powered analytics to evaluate learners' abilities in terms of communication, problem-solving, and interpersonal skills [1]. The results indicated that AI-supported assessments were effective in increasing learners' engagement and providing more precise and personalized recommendations for skill development. Still, this research was dedicated to evaluating learners' soft skills and did not apply the digital twin approach to continuous modeling of their progress [2].

An AI-powered adaptive training platform for integrating Digital Twin-based skill gap analysis with future readiness assessment. The researchers used virtual representation of the learners for tracking their competency development and detecting skill gaps in real time [3]. The framework proved to be able to generate personalized recommendations for learning and career readiness. This research pointed out the benefits of the combined use of artificial intelligence and digital twins for personalizing learning, however, it mostly concerned the workforce training sphere.

The author explored trends in immersive learning environments with digital twin technology. In particular, the researchers considered the application of digital twins for creating realistic virtual learning spaces, which would promote learners' interactions, engagement, and experience. As a result, it was found that digital twin-supported immersive environments positively impacted knowledge retention and skill acquisition [4]. It should be noted that this paper stressed the importance of the growing role of digital twins in reshaping the educational ecosystem but paid little attention to deep learning approaches.

A survey on human-focused digital twin applications in occupational safety and health environments. The researchers have reviewed different types of digital twins that can track human behavior, performance, and wellness through real-time data gathering and analysis [5, 6]. According to their findings, digital twins helped enhance decision-making process, risk assessments, and personalization of support solutions. While this study was conducted in the workplace environment, it demonstrates the possibility of using digital twins in modeling human behavior and making adaptive interventions, which can be further used in educational settings.

Authors in [7-9] analyzed the use of Generative Artificial Intelligence and Digital Twins in educational settings to promote creativity and innovations among learners. They have considered the potential of digital twins to create dynamic educational scenarios along with generative artificial intelligence that will help generate personalized content, facilitate problem-solving, and provide adaptive education opportunities. The results of the research have demonstrated that the integration of these technologies promoted engagement, creativity, and knowledge building. Still, the research concentrated more on promoting learners' creativity and did not analyze real-time learners' analytics and prediction of academic performance [7].

Different authors analyzed the value creation process of Digital Twin-enabled services and the contribution of digital twins into decision-making process, personalization, and optimization of services [8, 9]. The study has shown that continuous synchronization of data between physical and virtual entities improves user experience and quality of services provided. Although the research is dedicated to service management, it demonstrates potential of digital twins for personalized educational services.

Authors in [9] investigated the applicability of Digital Twin technology in mining machinery education. The virtual representation of mining machinery has been created by researchers and has allowed students to interact with complicated machinery through simulation. The results of the research proved that educational systems based on the digital twin technology positively affect practical knowledge acquisition, increase learner engagement, and reduce the risks and expenses related to practical training. However, the study focused only on engineering education and did not use any advanced deep learning technology for learner modeling.

The study in [10] examined the role of the Digital Twin framework in smart manufacturing environments and evaluated its contribution to sustainability and operational efficiency. Statistical analysis has shown the ability of digital twins to facilitate real-time monitoring, predictive maintenance, and intelligent decision making. Thus, the results of the research have proved the potential of digital twins to analyze large amounts of data and support adaptive operations. Even though the study has been done for manufacturing systems, the results of the research are important for using digital twin technology in adaptive learning.

The study in [11] analyzed the role of the Digital Twin framework in sustainable smart manufacturing systems via statistical analysis. In particular, the authors have considered how digital twins facilitate real-time monitoring, predictive maintenance, resource optimization, and intelligent decision making within manufacturing environments. As a result, the research has proved significant improvements in the operational efficiency, sustainability, and adaptability of such systems. However, even though the focus of the research has been industry-related, the capability of digital twins to analyze large amounts of real-time data is very important for adaptive learning environments.

Another study in [12] presented a systematic evaluation of the impact of gamified cybersecurity training using behavioral learning approaches and digital twins. Specifically, the authors designed and tested a gamified training system based on digital twin technology, which simulated real-life situations of cybersecurity training and learners' activities. As a result, the combination of digital twins and gamified learning was proved to be highly effective in terms of increased user engagement, knowledge retention, practical skills development, and training efficiency. The paper revealed the capabilities of digital twins in building adaptive learning environments but did not use any deep learning approaches for building personalized models of learners and predictive analytics.

Researchers in [13] assessed the effectiveness of a Digital Twin Learning System (DTLS) in engineering education, particularly in landscape architecture courses. The authors designed an educational system based on digital twin technology, which provided students with the ability to visualize and simulate learning environments in real-time. As a result, the use of DTLS led to better learning performance in terms of understanding, knowledge acquisition, engagement, etc., compared with traditional instructional methods [14]. The paper showed the value of the educational use of digital twins but focused mostly on simulation-based learning and not on personalized learner analytics and recommendations.

Table 1 presents a comparison of the major Digital Twin-enabled personalized learning approaches, their methodologies, application domains, key contributions, and limitations. The table helps to put the proposed Digital Twin-Enabled Personalized E-Learning Framework in the context of other research studies.

It is noted from the comparison that the current Digital Twin based education approaches have shown significant potential in improving the level of engagement of learners, the development of skills, the level of immersive Ness, and the provision of personalized support for education. The majority of the studies have highlighted areas including workforce training, engineering education, cybersecurity training, creative learning, and technical skill development. These methods were effective in utilizing the Digital Twin technology for simulation, monitoring, and adaptive support, but they did not fully incorporate AI tools such as deep learning and real-time learning analytics.

Table 1. Comparative Summary of Existing Digital Twin-Enabled Personalized Learning Approaches

Author (Year)	Method / Model	Application Domain	Key Contribution	Key Limitations
[20]	WiseWorldAI: AI-Driven Assessment Platform	Soft Skill Development	Provided intelligent assessment and personalized feedback for soft skill enhancement	Focused only on soft-skill assessment, lacked digital twin-based learner modeling
[21]	AI-Driven Adaptive Training Platform with Digital Twin	Workforce Training and Skill Development	Performed skill-gap analysis and future-readiness assessment using learner digital twins	Limited to professional training environments
[22]	Digital Twin-Based Immersive Learning Framework	Immersive Education	Enhanced learner engagement and experiential learning through virtual learning environments	Limited integration of deep learning and learning analytics
[23]	Human-Centered Digital Twin Framework	Occupational Safety and Health	Enabled real-time monitoring of human behavior and performance	Not specifically designed for educational applications
[24]	Generative AI and Digital Twin Integration	Creative Learning Environments	Improved creativity, personalized content generation, and adaptive learning experiences	Did not address performance prediction or learning analytics
[25]	Digital Twin-Enabled Service Framework	Service Management	Enhanced personalization and decision-making through continuous data synchronization	Focused on service systems rather than e-learning
[26]	Digital Twin-Based Technical Training System	Mining Machinery Education	Improved practical learning, technical skills, and learner engagement	Restricted to engineering and technical education
[27]	Digital Twin Framework for Smart Manufacturing	Smart Manufacturing	Supported predictive analytics, real-time monitoring, and intelligent decision-making	Industrial focus, not validated in educational settings
[28]	Gamified Learning with	Cybersecurity Training	Improved learner engagement, knowledge retention,	Lacked deep learning-based

	Digital Twin Support		and training effectiveness	personalization mechanisms
[29]	Digital Twin Learning System (DTLS)	Engineering Education	Enhanced student understanding and learning outcomes through virtual simulations	Focused on simulation-based learning rather than adaptive personalization
Proposed Work	Digital Twin-Enabled Personalized E-Learning Framework using Deep Learning and Real-Time Learning Analytics	Personalized E-Learning Environment	Integrates learner digital twins, deep learning prediction models, real-time learning analytics, and adaptive recommendation mechanisms for personalized learning pathways	Computational complexity and real-time data processing requirements

The literature reviewed demonstrates the increasing relevance of Digital Twin technology for the development of smart and adaptive learning environments. These are typical areas of research using virtual learner representations, real-time monitoring systems, immersive learning environments, and AI-based personalization strategies. Most studies on this topic however are domain specific and focus mainly on simulation-based learning or skill assessment. Moreover, there has been little integration of continuous learner modeling, predictive academic performance analysis, adaptive recommendation systems, and real-time behavioral analytics in a single framework.

The present study tackles these limitations by introducing a Digital Twin-Enabled Personalized E-Learning Framework based on Deep Learning and Real-Time Learning Analytics. The proposed framework combines multiple features of continuous learner modeling, deep learning for performance prediction, real-time analysis of students' behaviors, and adaptive learning suggestions, to create a holistic personalized learning environment. The proposed system seeks to address certain limitations in the current literature and enhance the aspects of engagement, prediction, educational effectiveness, and adaptive decision making.

RESEARCH METHODOLOGY

The Digital Twin enabled Intelligent learning framework proposed in the study is an integrated approach of Deep Learning and Real-Time Learning Analytics that enables personalized learning experiences [15]. The methodology is divided into five phases: Data acquisition, Construction of digital twin, Deep learning-based prediction, Real-time learning analytics, Adaptive recommendation generation [16]. The framework can record ongoing learner interactions, update the learner's digital twin profile, forecast academic performance with the help of deep learning models, and design the personalized learning pathway.

Proposed Framework

These modules work together to form a comprehensive framework, which is made up of five connected modules. The framework (Figure 1) constantly integrates the data of the learner into the digital twin and creates personalized suggestions according to the learner's behavior and predicted academic performance.

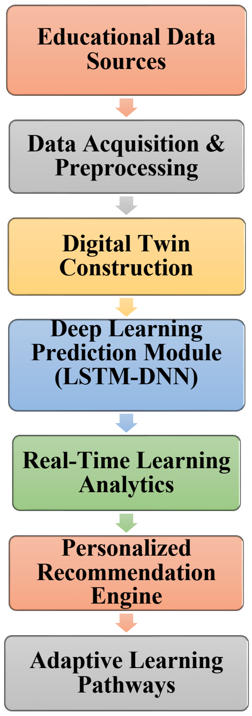

Figure 1. Framework of the Proposed Digital Twin-Enabled Personalized E-Learning System.

Phase 1: Data Acquisition

Educational data are collected from multiple learning environments and educational platforms, see Table 2.

Table 2. Educational Data Sources for Learner Modeling.

Data Source	Information Collected
Learning Management Systems	Course access, learning progress
Online Assessments	Quiz scores, assignment grades
Discussion Forums	Interaction and participation level
Learning Videos	Viewing duration and completion rate
Clickstream Logs	Navigation patterns and behavioral activities
Attendance Records	Class participation frequency

The data obtained are sanitized, normalized, and structured into learner profiles for analysis in the following stages.

Phase 2: Digital Twin Construction

Digital Twins (Table 3) for each individual learner are generated to represent their academic standing, learning behavior, engagement, and knowledge mastery [17].

Table 3. Components of Learner Digital Twin.

Component	Description
Demographic Profile	Age, educational background, program
Learning Behavior	Study patterns and interaction frequency
Academic Performance	Assessment and examination scores
Engagement Indicators	Participation and activity metrics
Knowledge Mastery	Subject-wise competency levels

The digital twin is continuously updated as new learner data becomes available.

Phase 3: Deep Learning-Based Prediction

A combination of LSTM and DNN algorithms is utilized for the analysis of learner behavior and forecasting of educational outcomes. The model predicts:

- Academic Performance
- Learning Engagement Level
- Course Completion Probability
- Dropout Risk
- Learning Progression Trends

Digital Twin-Based Personalized Learning Prediction Algorithm

To enable adaptive learning and personalization of educational interventions, the Digital Twin-Based Personalized Learning Prediction Algorithm was proposed. This algorithm gathers learning behavior data of the learner from various sources of education, creates a dynamic learner digital twin, and makes use of the hybrid LSTM-DNN structure to make predictions about the learner's academic success, engagement, and learning outcomes. These predictions are used to provide recommendations for learners to make adaptive paths of learning.

The proposed algorithm automatically gathers and preprocesses the data of the learner interaction with different educational platforms. A learner specific digital twin is then formed and continually updated with real time learning data. The features of the behavioural, engagement, and academic performance are extracted and processed by applying a hybrid LSTM-DNN model to predict the learning outcomes and detect potential risks. The system then utilises predictions and real-time analytics to provide personalised recommendations, adaptive learning materials and intervention strategies, enabling effective and individual learning experiences.

Algorithm 1. Digital Twin-Based Personalized Learning Prediction.

```
Input:
  D = Learner Dataset
Output:
  R = Personalized Recommendations

Begin

1. Collect learner interaction data from LMS and learning platforms.

2. Preprocess and normalize the collected data.

3. Construct learner Digital Twin (DT).

4. Extract behavioural, engagement, and performance features.

5. Train the hybrid LSTM-DNN model using extracted features.

6. Predict:
   • Academic Performance
   • Engagement Level
   • Course Completion Probability
   • Dropout Risk

7. Update Digital Twin using real-time learner data.

8. Generate personalized learning recommendations and adaptive interventions.

9. Deliver customized learning pathways.

10. Repeat until learning objectives are achieved.

Return R

End
```

Deep Learning Architecture

The proposed model is a hybrid Long Short-Term Memory (LSTM) and Deep Neural Network (DNN) model, which is used to analyze the behavior of the learners and predict their academic outcomes [18]. The LSTM component would learn sequential and temporal learning patterns from the interaction of the students and the DNN component would learn complex non-linear relationships between the education variables to make more accurate predictions. This hybrid architecture allows for effective modeling of learner engagement, learner performance progression, course completion probability, and dropout risk [19].

Input Layer

The input layer is responsible for collecting learner-based features using Learning Management Systems (LMS), quizzes, discussion forums, clickstream data, and learning analytics systems. Learner-based feature vector can be written as:

$$X = \{x_1, x_2, x_3, \ldots, x_n\} \tag{1}$$

Where:

- Xrepresents the input feature vector.
- $x_1, x_2, x_3, \ldots, x_n$denote learner behavior, engagement, and academic performance attributes.

LSTM Hidden Layer

The extracted features undergo further processing by the LSTM layer to detect sequential dependencies within the learning process. The hidden state of LSTM neural network is given by:

$$h_t = LSTM(x_t, h_{t-1}) \tag{2}$$

Where:

- h_t= Current hidden state at time t
- x_t= Current learner activity input
- h_{t-1}= Previous hidden state

The LSTM layer is very effective at modeling the progress of the learner through time by capturing relevant history and avoiding the issue of vanishing gradients.

Output Prediction Layer

The final learner outcome is predicted using the DNN output layer as:

$$\hat{Y} = f(W_h h_t + b) \tag{3}$$

Where:

- $\hat{Y}$= Predicted learner outcome
- W_h= Weight matrix
- h_t= Hidden state output from the LSTM layer
- b= Bias term
- $f(\cdot)$= Activation function

The output layer generates predictions related to learner performance, engagement level, course completion probability, and dropout risk.

Digital Twin Update Function

A Digital Twin is a virtual representation of each learner that is constantly updated, as real-time data of the learning process is captured and fed back into the system [20, 21]. As learners engage with a range of learning materials, such as online tests, discussion forums, learning videos and Learning Management Systems (LMS), new behaviors and performance data are fed into the Digital Twin model [22]. This constant synchronization between the virtual representation and the learner's actual school status, learning engagement, learning preferences, and learning mastery provides a true picture of what the learner is learning [23].

To keep the physical learner and the Virtual Digital twin consistent, the proposed framework uses an adaptive update mechanism via equation (4):

$$DT_t = DT_{t-1} + \alpha(L_t - DT_{t-1}) \tag{4}$$

Where:

- DT_t= Updated Digital Twin state at time t
- DT_{t-1}= Previous Digital Twin state
- L_t= Current learner data collected at time t
- α= Learning adaptation coefficient ($0 < \alpha < 1$)

The adaptation coefficient α regulates the speed of change of the Digital Twin model for new information of learners. A high αincreases the sensitivity of the Digital Twin to recent learner activities while a low value gives it more stability, focusing on the learning patterns of past activities [24].

This update mechanism continuously refines the Digital Twin based on the changes in learner behavior, academic performance and engagement characteristics [25]. This new Digital Twin is then used by the Deep Learning Prediction module and the Recommendation Engine to provide precise predictions of performance, identifying any potential learning risks and tailoring learning paths for individuals [26]. Thus, the Digital Twin update function is a very important function in the proposed e-learning framework, which helps to monitor learners in real time, to make decisions automatically and to personalize learning with intelligence [27].

Real-Time Learning Analytics Module

Real-Time Learning Analytics (RTLA) is a crucial component of the proposed Digital Twin-supported personalized e-learning system, as it is used to track learners' interactions and learning activities in real time [28]. The module gathers, refines and studies data from Learning Management Systems (LMS), online tests, discussion boards, learning videos, and clickstream interactions, to give actionable insights into learner behavior, engagement, and academic progress in real-time [29].

The proposed RTLA module is unique from traditional learner analysis-based methods which perform learner analysis periodically, allowing the system to continuously monitor the changes of learner performance and engagement [30]. The outputs of the analytics engine are used to update the learner's Digital Twin, to detect potential learning risks and to guide adaptive learning interventions [31]. In addition, the analytics results are used as inputs for the deep learning prediction model and recommendation engine, which is used to create personalized learning pathways and educational support strategies, see Table 4 [32, 33].

Table 4. Learning Analytics Indicators Used in the Proposed Framework.

Analytics Indicator	Purpose
Time-on-Task	Measures learner engagement and study duration
Interaction Frequency	Tracks learner participation and platform activity
Quiz Performance	Evaluates academic achievement and learning progress
Navigation Behavior	Analyzes learner movement across educational resources
Content Consumption	Monitors utilization of learning materials and resources
Forum Participation	Assesses collaborative learning and peer interaction

The chosen analytics indicators offer a holistic understanding of the learner's behavior and learning. For example, Time-on-Task and Interaction Frequency are used to measure learner engagement, Quiz Performance to measure knowledge acquisition and learning effectiveness. Likewise, Navigation Behavior and Content Consumption show learning preferences and patterns of using resources, and Forum Participation shows the pattern of collaborative learning participation [34].

The Real-Time Learning Analytics component can track these metrics and notify the teacher of those students who are likely to be at risk, student disengagement patterns, and when the student is likely to be at risk of poor performance and offer suggestions for interventions [35]. Consequently, the use of real-time analytics together with Digital Twin technology enhances the tracking of the learners, educational decision making, and creation of highly adaptive and personalized learning experiences.

Evaluation Metrics

The performance of the proposed Digital Twin-Enabled Personalized E-Learning Framework is evaluated using standard classification, prediction, and recommendation metrics. These metrics assess the effectiveness of learner performance prediction, engagement analysis, and personalized recommendation generation [36].

Accuracy

Accuracy measures the overall correctness of the prediction model and is calculated as equation (5):

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{5}$$

Where:

- TP= True Positives
- TN= True Negatives
- FP= False Positives
- FN= False Negatives

Precision

Precision evaluates the proportion of correctly predicted positive instances among all predicted positive instances.

$$Precision = \frac{TP}{TP+FP} \tag{6}$$

Recall

Recall measures the ability of the model to correctly identify positive instances.

$$Recall = \frac{TP}{TP+FN} \tag{7}$$

F1-Score

The F1-Score provides a balanced measure of Precision and Recall.

$$F1\text{-}Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{8}$$

Recommendation Accuracy (RA)

Recommendation Accuracy is used to measure the performance of the personalized recommendation system.

$$RA = \frac{Correct\ Recommendations}{Total\ Recommendations} \tag{9}$$

Mean Absolute Error (MAE)

MAE is used to measure the mean absolute deviation between the actual and predicted value.

$$MAE = \frac{1}{n}\sum_{i=1}^{n} | Y_i - \widehat{Y_i} | \tag{10}$$

Where:

- Y_i= Actual value
- $\widehat{Y_i}$= Predicted value
- n= Number of observations

Root Mean Square Error (RMSE)

RMSE measures the deviation of predictions from the actual value, which is calculated using the square root of average squared difference between the actual and predicted value [37].

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2} \quad (11)$$

All these above-mentioned measures evaluate the performance of the proposed personalized e-learning system.

Comparative Analysis

The proposed Digital Twin-Enabled Personalized E-Learning Framework will be compared to the conventional e-learning systems in terms of prediction accuracy, engagement level of the learners, effectiveness of the recommendations provided, learning outcomes, and capability of personalization, see Table 5.

Table 5. Comparison Between Traditional and Proposed E-Learning Systems

Feature	Traditional E-Learning	Proposed Framework
Personalization	Limited	High
Learner Modeling	Static	Dynamic Digital Twin
Performance Prediction	Basic Analytics	Deep Learning-Based
Real-Time Monitoring	Limited	Continuous
Adaptive Recommendations	Minimal	Intelligent and Personalized
Learner Engagement	Moderate	High
Decision Support	Reactive	Predictive and Proactive

The methodology proposed offers a complete framework for the integration of Digital Twin technology, Deep Learning and Real-Time Learning Analytics to improve personalization and learner engagement and to make teaching more effective in today's modern digital learning environments.

RESULTS AND DISCUSSION

This section shows the performance evaluation of the proposed Digital Twin-Enabled Personalized E-Learning Framework based on Deep Learning and Real-Time Learning Analytics. The framework was tested with the learner's interaction data gathered from online learning platforms. Four metrics were used to evaluate the proposed system: prediction accuracy, recommendation effectiveness, learner engagement, and course completion rate, and personalization metrics. The findings show the potential of the combination of Digital Twin with deep learning and real-time analytics to create adaptive learning environments.

Learner Dataset Distribution

A dataset of learners' interaction data was obtained from several e-learning platforms, and the effectiveness of the proposed Digital Twin-Enabled Personalized E-Learning Framework was assessed. Data consisted of information about learner engagement, assessment performance, course participation, content consumption, and learning progression. Learners were divided into five performance levels in relation to their academic performance, engagement and behaviour in relation to their participation in course completion to enable the learners to be evaluated comprehensively. The data set consisted of training and testing sets to ensure that the model was properly developed and validated.

The distribution of learner records by each performance category is given in Table 6. The largest number of training samples was high-performing learners (2,500) and moderate-performing learners (2,200) had the largest number of testing samples (900) respectively. The low-performing learners were represented by a sample of 1,800 training and 700 testing samples and the at-risk learners were represented by a sample of 1,500 training and 600 testing samples. Also, 1,000 training samples and 400 testing samples were associated with learners who dropped out of their courses.

Table 6. Distribution of Learner Records

Learner Category	Training Samples	Testing Samples
High Performers	2500	1000
Moderate Performers	2200	900
Low Performers	1800	700
At-Risk Learners	1500	600
Dropout Cases	1000	400
Total	**9000**	**3600**

The distribution of the different categories of learners was balanced, which allowed the proposed deep learning model to be trained with different learning behaviors and performance patterns. This multi-dimensionality allowed the framework to effectively capture variations in learner engagement, to accurately predict academic outcomes, to enable them to identify risk of drop out and to make tailored learning suggestions. This led to the dataset being used effectively to assess the accuracy of the proposed personalized e-learning system based on the Digital Twin and its adaptability.

Prediction Performance of the Proposed Model

The effectiveness of the proposed Digital Twin-Enabled Personalized E-Learning Framework was assessed by comparing the LSTM-DNN model with various baseline deep learning models, such as LSTM, DNN and CNN architectures. The following classification metrics were used to evaluate Accuracy, Precision, Recall, and F1-Score. These measures were chosen to evaluate the model's accuracy in predicting how well students do in the course, how engaged they are, the likelihood that they will finish the course, and the likelihood that they will drop out.

The relative performance of the evaluated models is shown in figure 2. The model proposed by using the hybrid approach of LSTM-DNN gave the maximum classification accuracy for all the evaluation metrics. In particular, the model achieved an accuracy of 95.2%, precision of 94.7%, recall of 95.4%, and F1-score of 95.0% which are better than the stand-alone LSTM model, DNN model and CNN model.

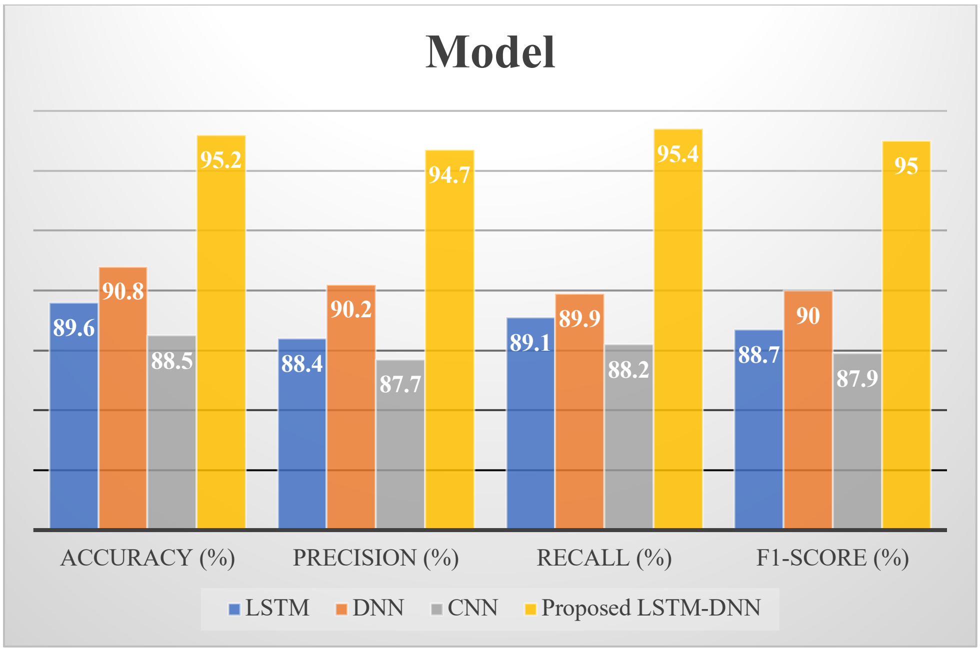

Figure 2. Prediction Performance Metrics

The effectiveness of the proposed model is due to the combined merits of LSTM and DNN structures. The LSTM part was able to capture sequential learner behavior and the temporal learning patterns, and the DNN part was able to model complex nonlinear relationships among the educational variables. This hybrid learning capability allowed for more precise prediction of the learner's outcome and engagement characteristics.

The results show that the developed DT model combined with deep learning can greatly improve predictive accuracy in a personalized e-learning environment. Moreover, the high recall value shows the effectiveness of the model in identifying learners in need of academic support, while the high precision value shows the effectiveness of the model in reducing the number of learners who are incorrectly identified. In general, the results substantiate the proposed LSTM-DNN model for intelligent learner monitoring, prediction and decision making in education.

Learner Engagement Analysis

One of the most important measures of the effectiveness of personalized e-learning environments is learner engagement. The Real-Time Learning Analytics module has been used to continuously track important engagement metrics before and after Digital Twin-based personalized recommendations were introduced, to assess the effects of the proposed framework. This analysis included the learner participation, use of resources, interaction rate, and length of time spent studying to evaluate how effective the adaptive learning interventions had on the overall learner engagement.

The impact on learner engagement due to personalized learning recommendations is shown in table 7. These findings show that the implementation of the proposed framework has led to significant improvement in all indicators of engagement. Average time spent learning went from 34.8 minutes to 52.7 minutes, showing that more time was being spent engaging with learning and holding attention to the educational content.

Table 7. Learner Engagement Indicators

Indicator	Before Personalization	After Personalization
Average Time-on-Task (minutes)	34.8	52.7
Course Interaction Rate (%)	65.4	84.3
Discussion Participation (%)	48.7	73.1
Resource Utilization (%)	59.2	81.5

Likewise, the course interaction rate increased from 65.4% to 84.3% which indicates more involvement in learning activities and interactions with the platform. There was also a significant increase in the participation of the students in the discussion forum from 48.7% to 73.1%, which reflects improved collaborative learning and student interaction. Moreover, the resource utilization rose drastically from 59.2% to 81.5%, showing a positive engagement and a usage of the recommended personalized learning materials by the learners.

The results suggest that the Digital Twin, Deep Learning, and Real-Time Learning Analytics (RTA) approach was able to improve the engagement of the learner by providing personalized learning paths. The results further support the ability of the proposed framework to support active participation, enhance learning motivation, and develop a more personalized and engaging learning experience.

Academic Performance Improvement

In the context of the proposed Digital Twin-Enabled Personalized E-Learning Framework, the goal to improve academic performance of the learner in the learning pathway using adaptive learning pathways and personalized recommendations was one of the main targets to be achieved. To evaluate its effectiveness, the performance of the learners in the proposed framework was compared with that of the traditional approaches of e-learning. The comparison was based on several academic measures such as quiz scores, assignment completion rates, final grade scores, and success rates of the course.

The comparative analysis of learner academic performance in traditional learning environment and the proposed personalized learning environment in e-learning is presented in Table 8. The findings show that, after implementing Digital Twin-based personalization and adaptive learning strategies, there was a significant improvement for all academic performance indicators.

Table 8. Academic Performance Comparison

Metric	Traditional Learning	Proposed Framework
Average Quiz Score (%)	72.6	86.8
Assignment Completion (%)	74.3	90.1
Final Assessment Score (%)	75.8	88.4
Course Success Rate (%)	71.2	89.7

Learning using the conventional approach was successful in attaining an average score of 72.6% in the quiz while the proposed approach attained an average score of 86.8% in the quiz which shows the improvement in knowledge acquisition and concept understanding. In relation to assignment submission, there was an increase in the submission rate from 74.3% to 90.1%, which indicates that the learners were highly motivated and engaged in the activities of the course. Moreover, the academic achievement was highly enhanced as seen from the increase in the average final assessment score from 75.8% to 88.4%.

Additionally, there is an indication of an increase in the success rate of the course from 71.2% to 89.7%, which indicates the influence of personalized learning pathways in the learning process and in course success. The use of Digital Twin architecture has led to improvements, which emanate from continuous monitoring of the learner's performance and recommendations for improvement.

Generally, the findings have shown the high positive impact of the proposed framework on academic achievement as it ensured individualized learning according to learners' need and preferences and their performance level. Therefore, it has confirmed the applicability of the combination of Digital Twin Technology, Deep Learning and Real-Time Learning Analytics.

Recommendation System Performance

A central element of the proposed Digital Twin-Enabled Personalized E-Learning Framework is the recommendation engine, which generates adaptive learning materials, customized testing/assessment and intervention approaches, according to the learner profile and forecasted results. To gauge its effectiveness, the recommendation system was checked for recommendation accuracy, recommendation acceptance rate, resource relevance score and learner satisfaction.

The analysis of the proposed recommendation engine is given in Figure 3. The recommendation accuracy was 93.8%, which shows that most of the suggested learning resources and activities were relevant to the need and learning objectives of the learners. In addition, the rate of learner acceptance of the recommendations was 89.5%, which indicates that the system provided learners with adaptive learning pathways and recommended materials that were used.

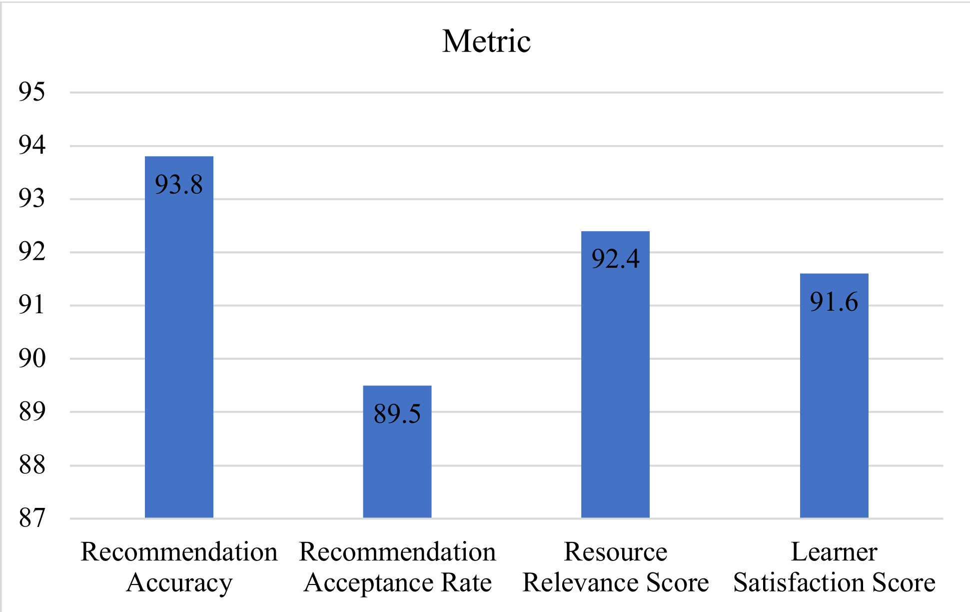

Figure 3. Recommendation Performance

The resource relevance score of 92.4% was obtained, which demonstrates the capability of the recommendation engine of aligning educational resources with the individual learners' profile, knowledge and learning preferences. Moreover, the score for learner satisfaction is 91.6%, which points to a high level of user acceptance, showing a positive perception about the personalized learning experience provided by the framework.

The results show that the combination of Digital Twin technology, Deep Learning and Real-Time Learning Analytics made a significant impact in the effectiveness of the recommendation process. The system could continuously analyses and update profiles of digital twins of learners to provide highly relevant and personalized educational content. As such, the proposed personalized e-learning environment achieved higher levels of learner engagement, learning effectiveness and learning outcomes thanks to the recommendation engine.

Course Completion and Dropout Prediction

Accuracy prediction of the outcome of completing courses and identifying those at-risk learners of being dropouts is very important in improving retention rate and educational outcomes. The proposed framework of digital twin-enabled personalized e-learning uses real-time learning analytics and deep learning prediction models to enable continuous monitoring of the learner's behaviour and thus enabling interventions to be made. The performance of the prediction model was evaluated using four key parameters, completion prediction accuracy, dropout prediction accuracy, early risk detection, and intervention success rate.

The performance of the proposed framework on predicting the course completion and dropout of the learner are presented in Table 9. The framework successfully predicted the progress of learners with an accuracy rate of 94.3%, what this means is that the framework is a good predictor of learner progression and effective in course completion. Likewise, a drop-out prediction accuracy of 92.7% was achieved, which shows its ability to predict the dropouts.

Table 9. Course Completion Prediction Results

Metric	Proposed Framework
Completion Prediction Accuracy (%)	94.3
Dropout Prediction Accuracy (%)	92.7
Early Risk Detection Rate (%)	91.8
Intervention Success Rate (%)	88.6

Considering the early risk detection rate of 91.8%, it highlights the effectiveness of both Digital Twin and Learning Analytics components in detecting any risk signals related to learners' disengagement at the initial level. Additionally, the successful implementation rate of interventions at 88.6% demonstrates that the recommended actions and intervention strategies generated through the framework have been successful in improving retention of learning.

From the results obtained, it is evident that the suggested framework could be used to facilitate proactive learner retention through continuous monitoring of learners' behavior and risks prediction with the application of appropriate interventions. Consequently, it increases the chances of course completion rate.

Confusion Matrix Results

A confusion matrix was also used to calculate the classification accuracy of the proposed hybrid LSTM-DNN model. The confusion matrix gives a detailed analysis of the model and its ability to correctly classify the learner outcomes by showing the true positives, true negatives, false positives, and false negatives. This analysis contributes to the determination of the effectiveness of the proposed framework in predicting the learner performance and identifying the at-risk learners.

Table 10 shows the confusion matrix results from the proposed model. Of all the positive cases, 1185 learners were correctly identified as positive, and just 65 learner cases were incorrectly identified as negative. Likewise, for the negative instances 1298 learners were correctly classified negative while 52 instances were incorrectly classified as positive.

Table 10. Confusion Matrix of Proposed Model

Actual Class	Predicted Positive	Predicted Negative
Positive	1185	65
Negative	52	1298

The comparatively small number of false positives and false negatives suggest the effectiveness of the proposed hybrid LSTM-DNN architecture in correctly categorizing various learners. The high accuracy rate of the correctly classified instances indicates the good predictive power and reliability of the model in predicting educational outcomes.

Overall, the confusion matrix outcomes confirm the effectiveness of the proposed framework for Digital Twin, with high rates of true positive and true negative, and a low number of classification errors. The results also demonstrate the suitability of the framework in conducting predictions that learners' performances could be predicted for the purpose of determining students' drop-out risk and identifying personalized educational intervention strategies.

Comparative Analysis with Traditional E-Learning Systems

For the overall effectiveness of the proposed Digital Twin-Enabled Personalized E-Learning Framework, it was compared to a traditional e-learning system. The comparison was based on certain educational and technological features such as personalisation ability, learner modelling, prediction model, monitoring, recommendation intelligence, learner engagement, course completion, and prediction accuracy. The goal was to understand how much the proposed framework enhances adaptive learning and learning results.

A comparative performance of traditional e-learning systems and proposed framework is shown in Table 11. The results show very significant gains in all the evaluation criteria. Most traditional e-learning platforms have a fixed profile for each student, and simple analytics methods, which could provide limited personalization and adaptive assistance. The proposed framework, however, uses a Dynamic Digital Twin framework, along with Deep Learning and Real-Time Learning Analytics, to monitor and track the learner behavior continuously, and give customized learning experiences.

The results showed that the course completion rate improved from 74.2% in the traditional e-learning to 90.3% under the proposed course, with an adaptive learning pathway and timely intervention strategies proving to be effective. Likewise, the prediction accuracy of the hybrid LSTM-DNN model is also seen to have improved substantially from 82.4% to 95.2%, showing the excellent performance of the hybrid model in predicting learner performance and detecting at-risk learners.

Moreover, the proposed framework provides enhanced real-time monitoring and intelligent recommendation generation for proactive educational support and resource allocation. The use of such skills helped to increase participation of learners, achieve better academic results and facilitate effective learning.

In summary, the comparative analysis shows that the proposed Digital Twin-Enabled Personalized E-Learning Framework is significantly better than traditional e-learning systems in various aspects, such as personalization capabilities, predictive intelligence, learner engagement, and academic outcomes. The results confirm the ability to establish adaptive and intelligent learning environments by combining Digital Twin technology, Deep Learning and Real-Time Learning Analytics.

Table 11. Comparative Analysis of E-Learning Systems.

Feature	**Traditional E-Learning**	**Proposed Framework**
Personalization Level	Low	High
Learner Modeling	Static	Dynamic Digital Twin
Performance Prediction	Basic Analytics	Deep Learning-Based
Real-Time Monitoring	Limited	Continuous
Adaptive Recommendations	Limited	Intelligent
Learner Engagement	Moderate	High
Course Completion Rate (%)	74.2	90.3
Prediction Accuracy (%)	82.4	95.2

The experimental results show that the combination of Digital Twin technology, Deep Learning and Real-Time Learning Analytics significantly improves personalized learning. The hybrid LSTM-DNN model demonstrated the best prediction results and the Digital Twin mechanism allowed continuous monitoring of the learner and the generation of adaptive interventions. Moreover, custom-made suggestions boosted learners' engagement, learning outcomes and course completion rates. The results confirm that the proposed scheme is an effective and intelligent adaptive e-learning system that enables the individualization of learning and facilitates decisions for educational activities based on data.

SUMMARY AND CONCLUSION

The suggested Digital Twin-Enabled Personalized E-Learning Framework comprises Deep Learning and Real-Time Learning Analytics to improve personalization, learner engagement, academic performance, and educational decisions. The suggested framework relied upon learner digital twins for continuous modeling of learner behavior, engagement patterns, academic progression, and level of knowledge acquisition. The hybrid LSTM-DNN framework managed to attain high prediction accuracy for learner performance, course completion, engagement, and risk of dropout, as well as giving high-quality recommendations on learning materials.

Experimentation results indicated that the suggested framework performs effectively in all aspects of evaluation. The hybrid LSTM-DNN framework achieved a prediction accuracy of 95.2% for learner performance and other learning parameters, outperforming traditional deep learning methods. Time spent, interaction in course activities, participation in discussion forums, and resource utilization demonstrated the capability of real-time learning analytics to enhance learner engagement. Moreover, personalized learning pathways resulted in improvements in learning outcomes, assignment completion, final assessment grades, and overall course success rates. Recommendation accuracy and learner satisfaction were also high, indicating the effectiveness of the recommendation engine in providing relevant educational materials. Comparative analysis further revealed that the proposed framework outperformed conventional e-learning systems in terms of personalization capability, predictive intelligence, learner monitoring, and educational outcomes. The integration of Digital Twin technology, Deep Learning, and Real-Time Learning Analytics enabled continuous learner modeling, proactive educational support, and the creation of an intelligent and adaptive learning environment. Overall, the results confirm the effectiveness of Digital Twin-based personalized e-learning systems in improving learner retention, engagement, academic performance, and the overall effectiveness of the learning process in modern digital education.

The novelty of this research lies in the development of a unified Digital Twin-enabled personalized e-learning framework that integrates dynamic learner digital twins, a hybrid LSTM-DNN predictive model, and real-time learning analytics within a single adaptive architecture. Unlike conventional personalized e-learning approaches that rely on static learner profiles or offline analysis, the proposed framework continuously updates learner digital twins using multimodal learning data to provide predictive learner modeling, proactive interventions, adaptive learning pathways, and personalized recommendations in real time. This integrated approach demonstrates superior predictive performance and educational outcomes while establishing a scalable foundation for next-generation intelligent e-learning systems.

Future work should focus on several important directions. Seamless integration with existing Learning Management Systems (LMS) should be enhanced to enable continuous learner monitoring, adaptive content delivery, and personalized learning support without disrupting existing educational infrastructures. In addition, advanced Artificial Intelligence techniques, including Transformer-based architectures, Generative Artificial Intelligence, and Reinforcement Learning, should be incorporated to further improve prediction accuracy, recommendation quality, and adaptive decision-making capabilities. Future research should also extend real-time analytics by incorporating cognitive, behavioral, and emotional learning indicators to provide a more comprehensive understanding of learner states and improve risk assessment. Finally, the scalability and generalizability of the proposed framework should be validated across diverse educational environments, academic disciplines, institutional settings, and learner populations to establish its robustness and practical applicability in large-scale digital learning ecosystems.

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CONFLICT OF INTERESTS

Authors confirm that there is no conflict of interest associated with this publication.

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