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A Reinforcement Learning-Based Smart Educational Environment for Higher Education

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ABSTRACT

Most higher education institutions use unique technologies to improve learning activities and provide comfortable learning. Higher education in a smart education environment (SEE) uses various tools and procedures to develop a smart learning environment to improve learning efficiency. Still, these learning processes fail to analyze student knowledge and cognitive features. The inappropriate identification of student learning skills affects teaching and learning quality. This problem is overcome using digital smart classrooms that support the student learning features because social factors and student personal behavior affects learning efficiency. So, the SEE should adapt student variability factors and learning strategies. In this work, reinforcement learning (RL) is utilized to create smart and comfortable learning in a smart classroom. The RL method analyses student behavior change, learning materials, and technologies that improve the overall learning efficiency. The created smart learning classroom achieves benefits of e-learning like interactions, flexibility, and experience.

KEYWORDS

Digital Classroom, Higher Education Framework, Learning Technologies, Reinforcement Learning, Smart Education Environment

INTRODUCTION

In a smart education environment (SEE) (Abdel-Basset et al., 2019), digital learning provides enormous instructional practice to students to improve their learning ability. Smart learning uses various educational technologies such as flipped learning, blended learning, personalized learning and adaptive learning strategies (Cheung et al., 2021) to manage teaching quality. These learning technologies depend on digital tools that are varied according to the degree of learning. The digital learning concept (Confrey et al., 2018) is a little complex, enhancing the overall learning experience. In addition to this, the smart learning process saves instructor time and provides a better relationship between the teacher and student, ensures transparency and is easy to track student learning progress (Felten et al., 2019). Therefore, most instructors give positive feedback for digital learning in a smart education environment. The smart learning process has several challenges(Rapanta et al., 2021), such as too many digital tools for teaching/learning, requiring new instructional approaches, lack of time, accessing technologies at home, lack of digitized curriculum, lack of parent involvement, and collaboration with educators etc.

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These problems are overcome by integrating digital learning in the classroom (Zainuddin, 2018), achieved via the flipped classroom, gamification and formative assessment. In the flipped classroom (Cevikbas et al., 2020), the learning is changed with the help of technology. The interactive environment (Liu et al., 2019) is created using the software and Wi-Fi connection. The teachers gather the student's responses according to the requirement at any time. Google software suite, seesaw, etc., are examples of the flipped classroom (Brueggeman et al., 2020). The next concept is gamification (Alt et al., 2020) which helps to boost creativity, social skills, teamwork, problem-solving skills and cooperation. The game-based classroom environment uses game-design thinking that feels classroom different and buzzing (Papadakis et al., 2019). Here, rewards are given to the winner, which boosts the student's learning ability and gives positive thoughts while facing the challenges. Classcraft, classdojo, play brighter are a few examples of gamification (Chusavitina et al., 2020). The last digital learning classroom is formative assessment (Barana et al., 2021). The classroom uses a checklist, questionnaires, and quizzes to analyze students' mindsets, thoughts, and ideas. The gathered information is more powerful in identifying the teachers/learners in the next direction (Hasan et al., 2021). In addition to this, the digital learning process minimizes the teacher's time for making the test-taking and online assignments. The teachers can create productive tasks and less plan with minimum effort and maximize the overall teaching efficiency. It is important to note that learning in digital environments is characterised by the availability of learning resources that can be accessed at any time, regardless of region. In addition, digital learning environments offer digitally altered teaching and promote educational possibilities for all groups of learners.

Considering these smart learning advantages in the classroom, different researchers focus on the various educational technologies to create an effective learning system (Uskov et al., 2017). However, most higher education (HE) institutions move toward the e-learning concept in the present pandemic scenario (Dai et al., 2021). The navigation from books to technologies creates a great impact in higher education. The smart learning process covers almost the entire learning into an online mode like teaching staff, students and other important education fields like publishers, learning technologists and librarians. Smart learning in the classroom requires an effective teaching policy because students' mindsets, behaviour and cognitive analysis continuously change. The existing tools, techniques, and modelling strategies do not concentrate on student behaviour and cognitive feature change. Therefore, an effective learning mechanism is introduced to improve the learning skill in the classroom. To achieve this goal, the Reinforcement Learning (RL.) framework is introduced to increase the learning ability in the smart classroom. The RL approach analyzes the student's state and behavior according to the 19 factors. These factors are helpful to understanding the student behavior, learning strategies and requirements effectively. RL is applied to generate smart and comfortable learning in a smart classroom. The R.L. method explores student behaviour change, student learning materials and technologies that increase the overall learning efficiency. The RL created a smart learning environment in the classroom that achieves benefits of e-learning like interactions, flexibility and experience. In addition to this, the algorithm uses the state-action-reward (SAR) concept to improve the overall e-learning process in the classroom.

This article is structured as follows: Section 2 discusses the different researcher's opinions on the digital learning process. Section 3 analyses the working process of RL framework based smart learning in the classroom, and the system's effectiveness is evaluated in section 4. The conclusion is described in section 5.

BACKGROUND

This section discusses the perspectives of several researchers on the smart educational environment for higher education. (Dai et al., 2021), using the analytic hierarchy method and evolutionary backpropagation neural networks to measure higher education students' smart learning. This work offers a comprehensive evaluation approach to address application effects and construction level challenges. The proposed analytic and fuzzy comprehensive strategy investigates the learning environment and offers construction recommendations. Student information collected from Central China Normal University assesses student learning using subjective factors. Completing the backpropagation learning process results in a learning space and improves fault tolerance.

(Alpaslan, 2021) explore a smart education approach for increasing students' educational objectives. The framework creates the educational design by leveraging information technology structures and layering architectural elements. The design includes lecture or course specifics that assist students in planning their future learning. In addition, many systematic analyses are carried out to improve the quality of the smart education system.

In a smart education system, (Bajaj et al., 2021) established artificial intelligence-based learning styles. Traditional learning systems employ the same learning patterns, which result in cognitive overload, disorientation, and a low level of learning efficiency. As a result, the issues are addressed by developing learning styles that are both adaptable and dependable for students. As a result, artificial intelligence approaches generate learning styles by comparing them to various learning models. The created learning style is deployed in the cloud to produce reliable, flexible, and scalable solutions in the smart learning environment.

(Kuppusamy et al., 2021) uses a machine learning model to make effective decisions in intelligent education systems. While educational administrators use the learning environment, this method seeks to decrease decision-making challenges. Because of the high-dimensional heterogeneous data, the typical system takes longer to produce results. The disadvantages are overcome by combining machine learning with a deep learning model. Deep learning produces patterns from learning data used to make successful decisions and recommend educational administrators in the quickest way possible.

(Ahad et al., 2018) used deep learning techniques for learning analytics in an Internet of Everything (IoE)-based educational model. The learning analytic system (LAS) investigates the learning degree and retention to provide improvements and corrective actions. To increase learning efficiency, the deep learning algorithm generates more valuable patterns. The developed system was tested using a feature-by-feature comparison of learner attainment, retention, cognition, and attention.

(Wang et a1., 2021) consider the Internet of Things (IoT) associated with smart educational learning methodologies to improve higher education. The key challenges in the education system include managing educational resources, which impacts educational quality. An IoT-assisted interactive system (IoT-IS) was designed to track student and teacher performance on the learning platform to address this issue. The requirements of the higher education system are studied using a psychometric procedure, and the active learning policy and attention scoring method are used to develop the interactive learning system. Furthermore, facial expressions are identified in online class videos, which aids in determining student actions with 98.5%.

(Sun et al., 2021) developed intelligent education systems based on the fuzzy knowledge graph and artificial intelligence (AI.). The fuzzy knowledge approach investigates the interaction between entities, methods, and instruments to construct effective educational frameworks. AI. approaches to building the framework based on entity, information, process design, and digitalized apprenticeship. The successful calculation of resources and entity relationships was used to create a supportive education system that covered theoretical and subjective backgrounds.

(Wanget al., 2021) used the hybrid deep architecture to evaluate a smart campus system. This work aims to reduce the problems in the E-learning behaviour prediction process. Academic information is gathered from Hohai University, and labels are assigned based on textual feedback. The gathered information is processed using bidirectional long-short term memory neural networks. The network examines data about subjective text analysis and the final answer screening phase. Furthermore, level-wise growing rules are used to cascade the information. The input cascading procedures allocate the labels for every input, improving the evaluation accuracy and reducing the complexity of traditional question and answer evaluation in smart campus systems.

(Alice Barana et al.,2021) proposes Interactive Feedback that leads a learner through the resolution of a problem after they have made at least one independent attempt at solving it. To improve student outcomes, we discovered that IF was more beneficial than other types of activities, and the impacts were particularly pronounced in low socio-economic circumstances.

From the discussions of many researcher's background studies in smart education environments, machine learning and deep learning approaches are used to increase learning efficiency. On the other hand, modelling strategies, tools, and procedures do not focus on students' knowledge level and cognitive features. The student's learning skills are affected when learning characteristics are generated incorrectly. Each student's learning characteristics and circumstances are unique, making it challenging to address while developing a framework. Furthermore, to improve the overall effectiveness of the education system, a smart learning environment requires comfortable learning patterns. As a result, an effective smart learning framework is created by considering the constantly changing student states and learning technologies.

REINFORCEMENT LEARNING (RL) FRAMEWORK FOR DIGITAL LEARNING IN THE CLASSROOM

Research Objective and Questions

The major goal of digital learning in the classroom is to improve online-learning options, inspire students to focus on their studies, increase in-person interaction, and eliminate infrastructural issues, lack of Education technology options for students who require special attention. In the classroom, digital learning delivers knowledge to students, and the smart learning process helps students and teachers maintain a positive relationship. Students may obtain material according to their needs through SEE, saving both time and money. Most research techniques are concerned with smart learning systems, and the following research questions are listed:

- How does the digital education process find a balance between learning data, teachers, and students?
- How does smart learning in the classroom employ communication technology to help students learn more effectively?
- How do you balance traditional classroom learning and digital learning in the classroom?

These research questions are considered while creating e-learning in the classroom environment. The digital learning process considers the smart device and focuses on real-life learning. The SEE should use adaptive learning procedures and technologies that help students absorb different knowledge, skills, and information effectively. Therefore, the research finds the learning procedures that include the formal, informal, positioned, personalized, collective and social learning concepts to improve higher education in a digital learning-based classroom environment. To achieve this goal in this work, RL examines student behaviour and current state. The RL approach predicts the particular situation and best possible behaviour that helps to create an effective learning system. In addition to this, the RL process sequentially decides solutions according to the present situation and previous criteria. Then the detailed working process of the Reinforcement Learning Framework based on adaptive and digital learning in the classroom is discussed below.

RL Based on Adaptive and Digital Learning in the Classroom

This section discusses the RL based on adaptive and digital learning processes in the SEE class environment. The framework has different components shown in figure 1; each component is interconnected with the student database and user interface.

Figure 1 illustrates that the framework for RL is based on digital and adaptive learning in the classroom environment. The digital framework explanation is described below:

- The student's static details like name, gender, and course, major are collected in the initial stage.
- All the collected details are stored in the interface and their current state is examined to improve the overall learning process. If the data entered is first time, then the static details are assigned to the students.
- The student data can be retrieved by analysing the current state with the list of suggested actions. Reward measurement helps to analyse the new state with the updated actions in the RL Framework.
- The student's database can be stored for further use.

First, the student's static details, such as name, gender, course, major, etc., need to be collected. Several dynamic details such as interaction level, state-action related reward history and log activities are collected. After collecting the student data, their current state should be examined to improve the overall learning process. If the student enters the first time into the learning process, then static details are assigned to the student. Then the reinforcement learning process is applied for generating the digital learning pattern according to the student's state. The actions are suggested to the students for improving smart learning. Here, the suggestions depend on their requests, such as learning materials and instructor pieces of advice in the video, audio or written format. The fourth component is rewarding analysis for specific actions according to the recommended actions. Here, the student satisfaction and interactivity levels are integrated to update the reward values. Students' next state and action should be computed to enhance the overall learning activities. The student may give negative rewards and suggestions that completely affect the quality of smart learning. The RL. framework reward-based system aims to maximize learning efficiency and improve satisfaction during learning. The successful utilization of the RL function process improves adaptive and personalized learning using the state-action-reward (SAR) computation. In addition to this, the RL framework balances the relationship between the student and teachers effectively. The working process of RL is described below.

Reinforcement learning (RL) works according to the biological system, interacting with surroundings and initiating learning. This work aims to maximize the rewards by providing the actions to the respective situation. The RL algorithm senses the environment to give optimal actions for the situation. The RL uses the exploration concept that effectively creates the online learning platform in an unsupervised environment. The working process of the RL framework is illustrated in figure 2.

The learning environment has a specific set of features defined as a state $s(t)$. Every $s(t)$ has a set of costs or rewards at a particular time t as $R(t)$. In RL in every instance, a specific action $A(t)$ is performed that affects the learning system state, which decides the next state condition. The $R(t)$ changes are determined based on the transition probability value that affects the learning system's next rewards. The RL process uses the previous experience to update the decision in future

Figure 1. Reinforcement learning-based digital learning framework

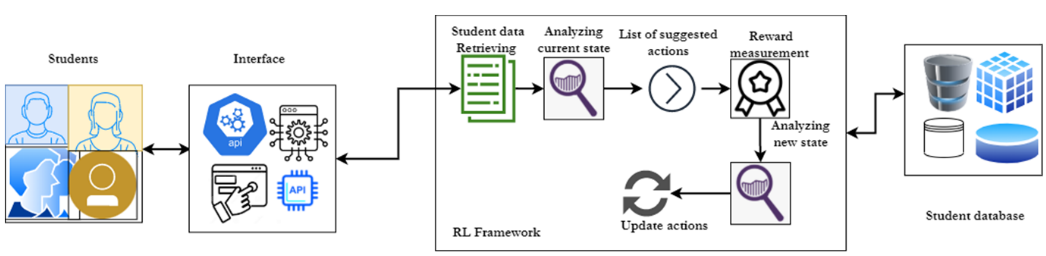
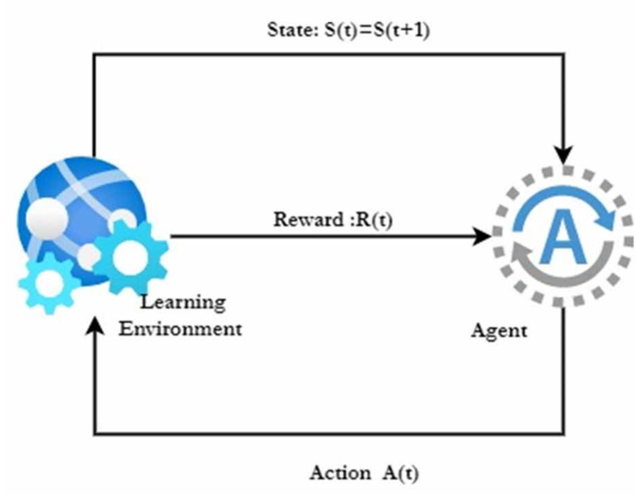


Figure 2. Reinforcement Learning (RL) Framework



actions during the action. The agent determines the action policies, states and other features by interacting with the environment. Here, dynamic programming and Monte Carlo methods are combined to solve the learning and prediction problem. As discussed, the RL framework uses the set of policies while allocating rewards for every action. The learning problem is solved by applying Q-learning, which uses the optimal policies to decide the environment. The optimal policy is selected based on the history of interactions in the learning environment. Here, the off-policy process is applied to identify the actions because no other policies suggest the actions in the smart learning environment. As said, the learning process generates new the reward r_{t+1} for state s_i and action a_i. The rewards are received by score estimation, and the Q-learning process is illustrated in eqn (1):

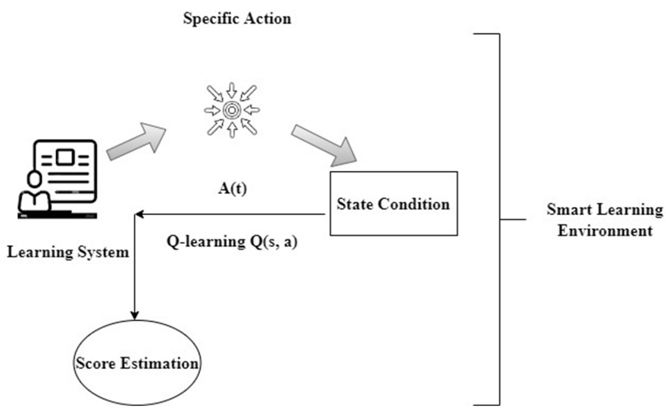
$$Q\left(s,a\right) = Q\left(s,a\right) + \alpha(r + \gamma \max a' Q\left(s',a'\right) - Q\left(s,a\right)) \tag{1}$$

In eqn (1), step rate is defined as α, the new state is s', reward value is r, future rewards discount factor is represented as $\gamma < 1 and$ $Q\left(s',a'\right)$ are the future rewards for specific action and state. The score estimation is denoted as s and the Q-learning process with the new reward generation is represented as a. The reward for the learning process is given as r, $Q\left(s,a\right)$ represent the current states score estimation. The step rate is can be estimated in the form of generation of new reward in the smart learning environment.

The Smart Learning Environment for score estimation is shown in Figure 3. The learning system with the specific action $A\left(t\right)$ is performed that affects the learning system state, which decides the next state condition with the Q-learning Q (s,a)

The learning environment has a specific set of features defined as a state $s\left(t\right)$. Every $s\left(t\right)$ has a set of costs or rewards at a particular time t as $R\left(t\right)$. In RL in every instance, a specific action $A\left(t\right)$ is performed that affects the learning system state, which decides the next state condition. The $R\left(t\right)$ changes are determined based on the transition probability value that affects the learning system's next rewards. The RL process uses the previous experience to update the decision in future

Figure 3. Smart learning environment for Score Estimation



actions during the action. The agent determines the action policies, states and other features by interacting with the environment. Here, dynamic programming and Monte Carlo methods are combined to solve the learning and prediction problem. As discussed, the RL framework uses the set of policies while allocating rewards for every action. The learning problem is solved by applying Q-learning, which uses the optimal policies to decide the environment.

According to the RL working process, SAR is constructed to make effective personalized and adaptive smart learning in the classroom environment. The SAR factors are created by measuring the several learning factors that should improve higher education performance. In this work, learning is integrated with several factors such as cognitive factors, personal factors, social factors, and structural and environmental factors. These factors are more useful to identify student behaviour and state change. Few factors are analyzed student-by-student; some other factors are concentrated on group-level analysis. These collaborative analysis helps to improve the digital learning criteria in the classroom. The collaborative analysis can be obtained from eqn (2):

$$Q\left(s',a'\right) = \alpha\left(r+\gamma\right) + r_{t+1} \tag{2}$$

In eqn (2), $Q\left(s',a'\right)$ are the future rewards for specific action and state, α is represented as step rate, reward value is represented as r, future rewards are represented as γ , t is denoted as time analysis for score estimation.

Along with this, static and dynamic factors should be considered because student mindsets and learning capabilities are changed from time to time. Here, student name, native language, age, and email are considered static characteristics; how students interact with the learning system is treated as dynamic characteristics. The static factors only concentrate on the initial stage of learning, and the dynamic factors are determined via the continuous learning experience and questionnaires. The dynamic factors are used to identify how the student adapts to the smart learning systems in the classroom. The student states are denoted as $X = \left\{x_1, x_2, \ldots\ldots x_n\right\}$. Here n is denoted as each state's dimensions. Every state has actions, and rewards are presented, and the rewards are computed based on the student's accepted level and long-term rewards. Based on the discussions few dynamic factors and related actions are described in table 1. The personal factors are in the form of frankness, righteousness, agreeableness, extraversion, Neuroticism. The style of learning include some of the state analysis like activists, theorists, reflectors, auditory, realists, numerical, language.

Table 1. Dimension of State-Action Analysis

Dimensions	State	Actions
Personal factors	Frankness	Reflective learning stylishness
	Righteousness	Randomly given any learning materials to the student
	Agreeableness	Assigning a few regular quizzes to improve the learning
	Extraversion	Discussing knowledgeable information
	Neuroticism	Giving enjoyable learning materials reduces anxiety and maximizes worthiness and self-esteem.
Style of Learning	Activists	Additional learning activities included in the existing projects
	Theorists	Test students to arrange their thoughts in sequence
	Reflectors	Analyzing the theory with real-life examples.
	Auditory	Giving video and audio materials to the students
	Realists	Giving searching tools and maps and informing students to write the action plan and algorithm.
	Numerical	Giving graphical analysis and numbers to improve the learning process
	Language	Graphical analysis, games, puzzles, and experiments enhance self-involvement.
Intellectual skills	Intelligence quotient	More attention to low I.Q. students
Previous educational accomplishments	Grade point score (GPA) in real-time subjects	More attention requires to low GPA value student
Motivation	Low/High	For communication and interactions, high motivation requires to improve the e-learning
Social capital	Low/High	Motivating the students by giving the social capital related materials
Term factors	Low/High	Mutual, cognitive, cohesion, safety, and related psychological materials are given to the students to improve the interactions.
Teaching factors	Low/High	Tools are given to establish the interaction between the teacher and students
Environmental factors	Respective adjustments	Noise, temperature, lightening related teaching materials are given to adjust the environmental factors

According to the above state-action analysis, a digital learning system is developed in the classroom environment to improve the overall learning process. The state-action related rewards are given to the students that are more useful to evaluate how the system achieves learning efficiency. Further, the research questions to be addressed to determine the efficiency of digital learning in the classroom. This state-action-reward based analysis is considered, and the digital learning process is created in the classroom using the following resources.

Resources for Digital Learning

The resources utilized in the digital learning process help meet the student learning goals in higher education. The resources provide guidelines for maximizing the teaching qualities, and it has been categorized into three types.

Simulation Analysis

The digital learning framework supports the simulations because it eliminates the actual implementations and improves the students learning ideas. Here, according to the Q-learning defined in the RL framework, the simulations are created to improve the overall learning process.

Animation

The digital format images are generated by considering the animation features in animation. The computer-generated images (CGI) consist of both dynamic and static images in which the animated images are treated as moving images. The animated images use real-time depiction, bandwidth and 3D graphics. The animation based learning improves the learning quality and features.

Quiz

The digital learning process uses the quiz to evaluate the student performance. The set of questions is utilized in a specific topic that helps investigate the student visibility, understanding, and acceptance of a particular concept.

E-Textbook

It is also named the digital textbook or electronic textbook. The student studying materials are published in a digitized format that includes images and texts. The materials are read-only with the help of digital devices, and devices require the software. Around 1000's books are published in a digitized format that minimizes the material cost.

Learning Objects

The important resource is the learning object named as the digital entities utilized to train and educate the students. The objects are very small, discrete and modular units of learning that deliver the content to the students in terms of digitized learning materials. The learning objects improve the student self learning, confidence and self-condenses.

Quantitative Research Analysis

The RL framework created a smart learning process analyzed using descriptive research analysis. Here the set of student information is collected from the previous state-action analysis for making the statistical analysis. The quantitative research analysis investigates the relationship between the previous learning characteristics such as population, student state, and behaviour with interactions between students and teachers. The smart learning experienced populations are selected from both student professors in higher education. To ensure the statistical analysis, random participants were also selected from students and teachers during the analysis. The collected population information is evaluated using the inductive and quantitative approaches. Quantitative analysis is used in the data collection and investigation process; data must be presented in numerical form. In the inductive research analysis, theories are applied to the data to identify the success rate of smart learning in the classroom.

Data Collection and Analysis

Data collection collects information according to the relationship between students' and teachers' knowledge of smart learning. In this work, Office of Institutional Research, Effectiveness, and Planning dataset information is utilized (https://irep.olemiss.edu/institutional-research/common-data-set/). Here, a set of questionnaires is utilized to gather the information because it helps determine the student's state and actions. The questionnaires collect information like gender, background, type of learning, internet connection types, classroom setup, time and duration. The created questionnaires determine students' acceptance of smart learning in the classroom. In this work, questions are asked to 548 population (including both students and teachers), of which 302 participants are female, and 246 participants are male. Around 83 samples utilize long-distance learning, and 447 use traditional (classroom) learning. Therefore, smart learning should be incorporated with classroom learning to improve the overall learning process. Among the participants, 201 populations have high experience, 216 populations have medium experience, and 14 do not have any experience on the Internet. 50 to 54% of people use the digital subscriber line (DSL) connection, ensuring the strongest link while creating smart learning. Around 2% of samples do not have any connection, and 3.4% of people only have a satellite connection because of the high expense. The research questionnaires are created in terms of three sections:

- The first step of the questionnaires is to form the student's self-efficacy and Internet experience, respectively.
- 2nd section is related to the student e-learning or smart learning experience and their attitude.
- The third section is organized in terms of demographic details.

These three questionnaires are formed by considering the table 1 state-action-reward details. Then the scale value is given from 1 to 7, where 7 is strongly agreed, and 1 is strongly disagreed. The gathered data is analyzed for verifying whether the student accepts the smart learning platform in the classroom environment. The student's behavior, attitude, and mental state affect their learning ability. Here, a traditional classroom or grading system is also considered to evaluate the effectiveness of the student's performance. Students post their reactions during the learning process to answer the teachers' questions. According to the student reactions and performance, scales are given from 0 to 10 for each student's skill and behaviour. The dataset consists of several skills related scales such as critical thinking & problem solving (SK1), creativity & innovation skills (SK2), constant & self-learning skills (SK3), collaboration & self-direction (SK4) and social & cultural responsibility (SK5). These skills-based online learning processes are initiated in the classroom environment, and students post their respective reactions. During the learning process, students are allowed to post 10 reactions per day to improve the overall learning process. The posts are confusing, amazing, bad, creative, collaboration, nice code, and helpful. Like this, each student post seven different emotions, but the reactions are limited to 10/ per day. The dataset is collected according to the classroom environment based on student activity and performance analysis. Then the sample dataset information is illustrated in table 2.

These created skills related information are formed by considering the table 1 state-action-reward details. Then the scale value is given from 0 to 10 for each skill class, and 0 or 1 is given for student's performance approval, where 1 is strongly approved, and 0 is strongly disapproved. The gathered data is analyzed for verifying whether the student accepts the smart learning platform in

Table 2. Sample information of digital learning based student reactions

	Total Post	Helpful Post	Nice code post	Collaborative Post	Confused Post	Creative Post	Bad Post	Amazing Post	time online	SK1 Classroom	Sk2 Classroom	Sk3 Classroom	Sk4 classroom	Sk5 Classroom	Approved
0	1	0	0	0	0	6	0	1	1600	2,1	2,4	3,5	3,6	1,7	0
1	1	0	0	1	0	2	0	3	592	0,3	0,3	0	0,1	0,2	0
2	2	4	3	9	0	16	1	8	1110	8	5	5	7	5	1
3	5	1	3	9	2	11	0	8	8651	6	5	4	6	4	1
4	14	6	15	28	0	50	0	45	34172	8,7	9	6,5	10	8,8	1
5	9	3	9	16	7	21	0	17	14985	5,1	6	5	7,5	8,6	1
6	15	10	21	21	1	34	0	37	25897	4,7	5	2	5	8,8	1
7	8	9	21	20	0	31	0	28	9476	5,3	5,7	4	5,7	8,4	1
8	6	3	12	13	0	24	0	19	43612	10	8,4	10	10	9,6	1
9	4	4	1	3	0	15	0	14	4791	2,3	2,6	1	2,9	7	0
10	5	1	3	6	0	16	0	20	18063	5,2	5,1	5	7,3	8,6	1
11	4	1	0	1	0	13	0	10	7269	5,8	6,7	7	6,7	8,4	1
12	4	3	1	4	0	21	0	19	8900	7,2	6	5	8,3	9,6	1

the classroom environment. The student's behavior, attitude, and mental state affect their learning ability. The gathered data and respective RL rewards clearly state that students who have a favorable attitude towards smart learning are more interested in learning the features via e-learning. The positive comments from the students also encourage teachers and instructors to improve the learning process. In addition to this, the collected data is investigated according to e-learning accessibility and self-efficacy. Then the rewarded values are utilized to analyze the student behaviour intention (BI) and adaptive learning (AL) in the classroom-based smart learning environment. Especially in higher education systems, the e-learning concept gives confidence and university support to the student to reach their goal. Then the RL framework-based e-learning process in a classroom environment is evaluated in the following section.

EVALUATIONS

The reinforcement learning framework's effectiveness is evaluated in this section. The data is analyzed and processed using the RL characteristics, and it is developed using the SPSS software (Sheikhaboumasoudi et al., 2018). The RL framework uses the 19 states and 19 actions defined in table 1. Then 19 dimensions based state-action matrix is generated, randomly created reward values and normal distribution values (standard deviation =1 and mean = 0). Here, the greedy policies are applied to select the maximum reward values, using the probability of policy value. During this process, reinforcement learning uses 0.1 as the learning rate, and the system gives both positive and negative reward values for actions. According to the defined simulation setup, 10 students' details are implemented using the 100 iterations. In the learning process, students provide positive rewards that increase the iterations. The positive reward value shows that smart learning is successfully implemented in the classroom.

This article uses the 548 student's information from environmental science classes (2009 and 2016) of OIRPE https://irep.olemiss.edu/institutional-research/common-data-set/ (26) (office of institutional research planning and effectiveness). This evaluation helps to understand how effectively student adapts digital learning in the classroom. In addition to this, performance difference between normal/traditional classroom learning and digitized classroom learning. Among the 548 students, 403 students utilize the existing classroom, and 145 use the smart learning classroom. Every student is treated as a single, static and discrete entity; students have four class ranks but do not have special learning criteria. The instructors have almost 10 years of experience in traditional and smart learning in the classroom environment. The existing classroom conducts 1 hour 15 minutes weekly twice. The smart learning classroom also uses the same teaching materials, but they desire to learn the system. The online student can spend more time learning the features and tasks and engage the student by giving the assessment.

The student study performance is evaluated using the GPA score and the actions mentioned in table 1. Student participation, homework, test and research projects are considered while calculating the score. The computed score values are transferred into the GPA letter. The effectiveness is evaluated using the chi-square analysis, t-test and ANOVA analysis. This analysis helps to understand the performance difference between normal and smart learning classrooms.

RESEARCH QUESTIONS AND ANALYSIS

Traditional and digitized classroom environments should balance the teachers and students while learning. The balancing factors are computed from the different dimensions such as intellectual skills, personal factors, social factors, motivation, previously experienced in learning etc. The balancing factors are derived from table 1, and respective answers are obtained via the questionnaires. The collected questions are processed with the help of state-action-reward (SAR) analysis. The collected results are processed by a Chi-square test that determines the balancing factor's performance in a traditional and digitized classroom environment. The Chi-square test is an effective statistical analysis test identifying the significant difference between expected and observed frequencies. The chi-square analysis identifies the relationship between the teaching performances in e-learning because the teachers should provide analysis and gather the resources according to the student requirement. The chi-square produces the values relevant to the difference between the teaching modality in two types of learning. If these two modalities are very low, then the smart learning classroom balances the student and teacher's relationship.

Table 3 illustrates the mean and standard deviation values of students who participated in the environmental science class via smart and traditional learning. The analysis clearly states the difference between e-learning and traditional learning systems. The grade value for classroom students achieves 69.35 mean values, and for smart learning students achieves 68.64 mean values. These values show that both learning concepts are similar, which means that the balance between the students and teachers is maintained successfully. Similarly, males and females also have a minimum mean value difference in their grade score points. Therefore, the two learning platforms are identical. The difference between the two groups is 0.33, which is fair to acceptable. The teachers formed the learning patterns and resources according to the student's mental and physical behavior. The reinforcement learning-based selected state-action-reward values to manage the balance between the teacher and student learning pattern. Then the chi-square test is accomplished in the SPSS software for identifying the grade difference between the traditional classroom and smart learning classroom teaching. Here, the student performance is evaluated using the grading system and obtained results of both learnings are shown in table 4.

Table 3 illustrates the academic performance analysis of the number of participants in this study. Around five grades such as A, B, C, D and F are considered to evaluate the student performance in the traditional classroom and smart learning. The traditional classroom learning environment has 403 participants, of which 28 students achieve an A grade, which is 6.94%. Similarly, a smart learning environment has 145 participants, of which 16 students ensure an A grade of 11.03%. Therefore compared to these two learning platforms, the smart learning system achieves higher academic performance. Here, the student's learning structure and characteristics are created according to their mental and physical state. Every state-action has a reward value that directly indicates that the e-learning classroom platform achieves better results. The effective utilization of reinforcement learning patterns in learning systems improves the overall efficiency and achieves the research

Table 3. Mean and Standard Deviation of Students

Variable	Smart learning (n=145 participants)		Traditional Learning (n=403 participants)		Male (n=246 participants)		Female (n=302 Participants)	
	Mean	Std.Dev	Mean	Std.Dev	Mean	Std.Dev	Mean	Std.Dev
Obtained Grade value	68.64	14.12	69.35	12.12	3.23	1.19	2.9	1.20

Table 4. Academic performance analysis for N-548

Analysis	A	B	C	D	F	Total
Traditional Classroom (TC)	28	120	131	50	72	403
TC in %	6.94	29.77	32.50	12.40	17.86	73.54
Smart learning (SL)	16	31	53	14	31	145
SL in %	11.03	21.38	36.55	9.66	21.38	26.45

questions. Further, the excellence of the learning systems is evaluated in gender using the chi-square analysis. The two groups and gender involved in the learning environment are illustrated in table 5.

In the two learning environments, gender-related academic performance is evaluated with chi-square analysis. The chi-square analysis is performed between the observed and expected values of the student performance in the learning environment. Here, 0.05 is taken as the default significant value while computing the difference between the two types of learning. Then the computed chi-square values are shown in Table 6.

In the chi-square analysis, 0.0546 values are obtained as chi-square statistics and 0.81532 as the p-value, insignificant at $p < 0.05$. This chi-square analysis clearly states no significant difference between traditional and smart classroom learning, and both learning environment provides successful teaching patterns to the students.

Then the ANOVA analysis is performed between these two learning platforms. The ANOVA analysis was used to identify the relationship between the learning patterns and features to identify the significance of learning. During the analysis, 10 students' performance in environmental science is taken, and the academic performance details are listed in table 7.

The above marks are obtained in environmental science, and the respective analytics is performed by computing the mean and standard deviation with a 0.05 significant value. Then the obtained results are shown in Table 8.

In table 8, the ANOVA analysis is performed for 10 students (N) by computing the mean and standard deviation values. In the above computation, the f-ratio value is 4.21849, and the p-value is .054805. The result is not significant at $p < .05$. Therefore, no significant changes in the traditional and smart learning classroom environment. F-ratio value is considered; the smart learning classroom-based students ensure higher results than traditional students. In the SL process, student needs and requirements are continuously analyzed according to the reward values. In addition to this, the t-test is

Table 5. Gender-based academic analysis

Learning Environment	Male	Female	Marginal Row Totals
Traditional Classroom	213	190	403
Smart Classroom	75	70	145
Marginal Column Totals	288	260	548 (Grand Total)

Table 6. Chi-square analysis of Gender-based academic analysis

Learning platform	Male	Female	Marginal Row Totals
Traditional Classroom	213 (211.8) (0.01)	190 (191.2) (0.01)	403
Smart Classroom	75 (76.2) (0.02)	70 (68.8) (0.02)	145
Marginal Column Totals	288	260	548 (Grand Total)

Table 7. Students Academic performance

LE	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
TC	80	85	89	90	92	94	95	96	89	89
SL	89	98	90	89	92	94	98	97	96	95

* LE-Learning Environment, TC-Traditional Classroom and SL-smart learning classroom

Table 8. ANOVA Analysis

Analysis	TC	SL	Total
N	10	10	20
ΣX	899	938	1837
Mean	89.9	93.8	91.85
ΣX^2	81029	88100	169129
Std.Dev.	4.8178	3.5839	4.5915

performed to determine whether the two learning platforms have significant differences or not when analyzing the student's academic performance. Here, 10 students' performance marks are considered to evaluate the significant difference. The obtained t-test computation is shown in table 9.

Tables 10 (a) and (b) show the student's performance in environmental science, which is obtained from table 6. The t-test is performed to identify the significant relationship between the learning parameters. For traditional classroom student performance, the t-test is computed by taking the difference value $\left(df_1 = N - 1\right)$, mean value M_1, squared difference SS_1. By using these values, the different source is calculated as $\left(SS_1 / \left(N - 1\right)\right)$. Therefore, student S1 obtain the 23.21 as difference score value. Similarly, the smart learning environment student performance was also obtained, and the result was 12.84. Finally, the t-test value is estimated using this difference between score value and student mean value $t = \left(M_1 - M_2\right) / \sqrt{S^2 M_1 + S^2 M_2}$. From the computation, the t-test value is -2.0539, and the p-value is 0.27402; therefore achieved result is significant at $p < 0.05$. According to the above analysis, the smart learning classroom has more advantages than the traditional learning process.

CONCLUSION

Thus the paper analyses the smart education environment based on higher education analysis. This work uses the reinforcement learning (RL) framework to investigate student characteristics. Traditional learning methods and tools fail to focus on the student's present situation and mental state. The improper identification of student requirements reduces the learning efficacy and academic performance. This research issue is solved by applying the RL approach that uses the state-action-reward analysis (SAR). The Smart learning patterns are created in the classroom environment by examining the student's present behavior, state, and condition used to improve e-learning. The SAR analysis uses a set of dimensional factors to determine the materials and learning strategies. The successful identification of these smart learning characteristics maximizes the overall learning efficiency and maintains the

Table 9. Results

Result Details				
Source	*SS*	*df*	*MS*	
Between-learning platform	76.05	1	76.05	$F = 4.21849$
Within-Learning platform	324.5	18	18.0278	
Total	400.55	19		

*SS-sum of the squares due to the sources, MS-mean sum of the squares due to the sources and df- degree of freedom.

Table 10.T-test Analysis

(a) Traditional Classroom environment			(b) Smart Learning Environment		
Students Performance (X)	Difference $(X - M)$ $M = 89.9$	Square Difference $(X - M)^2$	Students Performance (X)	Difference $(X - M)$ $M = 93.8$	Square Difference $(X - M)^2$
80	-9.90	98.01	89	-4.80	23.04
85	-4.90	24.01	98	4.20	17.64
89	-0.90	0.81	90	-3.80	14.44
90	0.10	0.01	89	-4.80	23.04
92	2.10	4.41	92	-1.80	3.24
94	4.10	16.81	94	0.20	0.04
95	5.10	26.01	98	4.20	17.64
96	6.10	37.21	97	3.20	10.24
89	-0.90	0.81	96	2.20	4.84
89	-0.90	0.81	95	1.20	1.44

relationship between the student and teachers. The relationship is evaluated using the chi-square, t-test and ANOVA analysis. Here, no significant difference happens between the two learning platforms. The no-significant means that the smart learning process ensures the valuable learning pattern is similar to traditional classroom learning patterns.

COMPETING INTEREST

The authors of this publication declare there are no competing interests.

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