Promoting Infrastructure Development through Experimental Learning in Law School Curriculum using Deep Learning Techniques to Improve Academic Performance

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Abstract: Academic performance improvements in law schools rely on theoretical and practical knowledge implications and assessments. The curriculum-based knowledge transfer and performance assessment are scrutinized to meet the societal factors in improving the student's knowledge. This article introduces an Experimental Learning Assessment Approach (ELAA) using deep learning for student academic performance improvements. The student's skills and assessments are performed using mock training and law sessions periodically with different stages. The assessments are carried forward using different sessions and integrated curriculum verification is performed. Based on this theoretical and mock practice assessment, the deep learning recommendation is used for performance amendments. The learning induces multiple assessment constraints considering the different stages and their difficulty levels. In this assessment, the individuals' output and the curriculum impact are used for framing different constraints toward performance validation. In this learning process, recurrent assessments for different stages and (new) constraints are exploited to improve the recommendations. Based on the recommendations, the curriculum implication, modification, or assessment frequency is persuaded.

Keywords: Academic performance; Curriculum recommendation; Deep learning; Experimental learning; Promoting Infrastructure Development
DOI: https://doi.org/10.14733/cadaps.2023.S15.274-293

1 INTRODUCTION

Law schools use various learning techniques and teaching techniques. Curriculum-based learning is mostly used in law school, providing certain syllabus to students. The curriculum is designed based on shapes and functions [19]. Features such as economic, cultural, political, and rights are the major priorities influencing the curriculum. Curriculum-based learning also includes fundamental skills such as problem-solving, counseling, communication, reasoning, factual investigation, and litigation [23]. Law schools provide proper skill sets which are necessary for a student. The curriculum provides important features which are required for a lawyer during schooling [3]. Curriculum design is a sequenced structure that provides certain instructions and functions to understand the content which are presented in the syllabus. Curriculum-based law schools increase learning and understanding performance and feasibility range [14]. Basic structure, legal research, negotiation technique, and legal analysis techniques are mostly presented in the curriculum, which reduces the complexity level in understanding the cause and source for the students [22].

Student performance improvement is a crucial thing to perform in every law school and university. Academic performance improvement is very important for law school students, which improves their overall skillsets of the students [21]. The main solution to improve academic performance is to conduct tests and exams for the students. Short-term educational goals are set in every law school that is calculated based on certain points and conditions [28]. Students' academic performance is evaluated by the papers and assignments provided by the students [12]. Curriculum grade point is provided to each student that produces feasible data for evaluation and calculation processes. Curriculum grade points contain the exact points scored by law school students [7]. Academic performance is also evaluated based on awards, grades, thesis, experience, honors, and academic points. Academic performance encourages students' courage and confidence range, which reduces the mistake ratio during learning and understanding [26]. Ranking methods and techniques are used in academic performance improvement, which identifies the exact skillsets of students. Academic performance is the major cause that improves law school students' quality and efficiency levels [6]. Infrastructure development plays a significant role in improving student academic performance in law schools and universities. To effectively assess and enhance student performance, a robust infrastructure is required to support various activities and processes

Deep learning (DL) techniques and methods are used in law school to improve students' academic performance range. DL technique is mainly used here to predict the drawbacks which are presented in teaching and learning processes [11]. Various concepts and techniques are provided to law schools that evaluate the performance range of students. The deep reinforcement learning (DRL) algorithm is used for prediction [25]. The feature extraction method is used in DRL that extract the important features and patterns which are presented in the curriculum and syllabus. The extracted features provide feasible data for evaluation and improvement processes [10]. DRL accurately predicts the features that provide necessary data for the performance improvement process. A deep neural network (DNN) algorithm is a law school that evaluates the educational qualification and skills of students. DNN uses a material recommendation technique that identifies the materials and variables of academic performance. DNN also uses a collaborative filtering technique that filters the patterns based on certain conditions and functions. DNN also provides effective improvement ideas to law schools that improve students' overall knowledge [6][8] [4].

2 RELATED WORKS

Li and Sun [17] designed an investigation approach to understand the rules in law schools. The proposed approach's main aim is to define rules for people in law schools. The proposed approach also provides the relationship between rules and thinking skills, which produce necessary skills for the students. Thinking skills provide certain understanding and knowledge in creating ideas and effects for a situation. The proposed approach improves the efficiency range in correlation, enhancing law students' knowledge skills.

Wang et al. [30] introduced a new student outcome evaluation method in law school. Both qualitative and quantitative approaches are used in the proposed method that maximizes the accuracy of the evaluation process. Student outcomes are collected from the management system, which provides feasible data for various processes. Student's behaviors and characteristics are also evaluated. Experimental results show that the introduced method improves law education's feasibility and efficiency range.

al Attar and Abdelkarim [1] proposed a decolonization method for international law. The actual goal of the proposed method is to decolonize the curriculum which is presented in law schools. A detection framework identifies the actual content and meaning of international law. The extracted datasets provide optimal information for the decolonization process. Decolonization examines important factors and features, which provides relevant data for further process.

Markovic and Gostojić [18] developed a legal document assembly system (LEDAS) for law school students. LEDAS is mainly used to enhance the legal drafting skills of students in law schools. Drafting provides the exact relationship between claims and input data which provides effective information on the case. The exact interconnections of data are identified by drafting skills which reduces complexity in understanding certain things. Practicing drafting skills is essential for young lawyers, which improves lawyers' performance and feasibility ratio.

Molontay et al. [20] proposed a data-driven probabilistic student flow approach for the curriculum prerequisite network. The main aim of the proposed approach is to characterize and categorize the curriculum based on certain functions. The proposed approach identifies the main courses and factors from the curriculum during degree time. The student flow approach simulates the effects and factors of the network. When compared with other approaches, the proposed predicts the properties of the prerequisite network for law school students.

Korayem and Alboghdadly [16] designed an innovative simulation-based education (SBE) approach. The proposed approach is mainly used to identify the impact of SBE on Advanced Pharmacy Practice Experience (APPE). Student assessment is used here that provide optimal data for evaluation and detection processes. The proposed approach is mostly used in every law school to identify the outcomes of students. Student assessment reduces the time and energy consumption range in computation, enhancing the systems' effectiveness and reliability.

Hall et al. [13] introduced a tri-constraint method for teaching generative construction scheduling. Statistical analysis is used here to predict the necessary characteristics and feedback presented in the database. The critical path method is also used here to analyze the important datasets available in the curriculum. Generative construction scheduling requires appropriate data, which reduces error and latency in the computation process. The introduced method ensures the efficiency level of teaching and learning systems.

Shanshan et al. [24] proposed a lean six sigma (LSS) framework based on big data analysis for curriculum systems. Big data analysis is used here to analyze the necessary data required for curriculum management systems. Knowledge graph analysis is also used here that identifies the important factors for further processes. Resources such as social, talent market, and technical requirements are improved in the curriculum. The proposed framework improves the curriculum system in higher education systems.

Deane et al. [9] developed a scenario-based assessment (SBA) to improve the curriculum in schools. An Automated Writing Evaluation (AWE) is used here that predicts the features and patterns for the evaluation and measurement process. AWE reduces the error range in the curriculum improvement process. Key values and variables are also extracted from the database, providing feasible data for curriculum improvement. The proposed approach maximizes the feasibility and efficiency ratio of curriculum management systems.

Uliyan et al. [29] presented a deep learning (DL) model for student performance evaluation. The Bidirectional Long Short-term Memory (BLSTM) algorithm and Condition Random Field (CRF) are used in the DL model. BLSTM detects the important features and factors that evaluate the retention and dropout of students. CRF identifies the sequence label of students from the outcomes. Experimental results show that the proposed DL model achieves high accuracy in student performance evaluation.

Shoaib et al. [27] developed a machine learning (ML) based prediction method for an educational institution. Educational Data Mining (EDM) is used here that extract the important features from the database. EDM reduces the time and energy consumption ratio in computation, enhancing the prediction process's efficiency. The behaviors and activities of students are predicted, which provides feasible data for the prediction process. Experimental results show that the proposed method maximizes accuracy in the education performance range of students.

Al-Ansi [2] proposed a student-centered format-based evaluation method for science, technology, engineering, and mathematics (STEM). Both qualitative and quantitative data analysis is used here that identifies the important objectives and patterns of STEM. The proposed method is mostly used for e-learning and e-assessment systems. The mixed method is used here that enhances the effectiveness and efficiency level of STEM institutions. The proposed method evaluates the exact content, which provides optimal data for further processes.

Carlson et al. [5] introduced improved student management and retention for portable learning technology. The main aim of the introduced method is to improve the quality and feasibility range in student management systems. Portable learning tools are used here that increase the knowledge of portable hardware platforms. Laboratory and library objectives are identified that provide necessary data for further processes. The introduced method measures both the direct and indirect effects of learning technology.

3 PROPOSED ASSESSMENT APPROACH

The ELA approach is designed to improve academic performance in the law school curriculum and is analyzed based on student skills and assessment stages. The assessment inputs are observed from the law students (i.e.) the theoretical sessions and mock training performance of the students in different stages are identified for improving their performance. This approach aims to reduce the difficulty in a theoretical and mock practice assessment. Using multiple sessions and integrated curriculum estimation is processed to improve the students' academic performance. From this assessment, the deep learning recommendation is aided for student performance corrections. The different assessment stages and difficulty levels are considered throughout the learning process and induce several assessment constraints in a particular session. The decidable factor is the individual's output and the curriculum impact of the students in law school is jointly analyzed based on weekly, monthly, and yearly academic performance assessments for different stages. The academic performance assessments are stored as records from the previously detected sequences for performance amendments. The proposed ELA approach improves the assessment frequency of the deep learning curriculum recommendation for law students. The multiple assessment constraints are controlled through academic performance validation for framing various constraints relies on better curriculum recommendations for correcting the student's performance. Some common curriculum data, such as students' behavior, activity, learning knowledge, memory, etc., are significant features in which the false negative, in this instance is to be thwarted through recurrent assessments. Curriculum recommendation is one approach that uses the learning process for classifying the student's assessment stages. The proposed approach is diagrammatically presented in Figure 1.

Analyzing academic performance in law school curriculum-based recommendation acquires theoretical and practical knowledge assessments and implications through deep learning for improving the student's knowledge. The student's skills and assessments are processed for deep learning recommendation using societal factors and recurrent assessments. The different stages and new constraints are exploited for augmenting recommendations. The deep learning result is used to compute current students' academic performance assessments through recommendations from the already stored data. The knowledge of law students is observed through academic performance (AP) using different sessions and integrated curriculum verification is computed. The observed curriculum is classified as theoretical and mock assessments. In theoretical assessments, the student's knowledge of the law curriculum is analyzed through academic performance, such as allocating exams in given time intervals for student academic performance improvements.

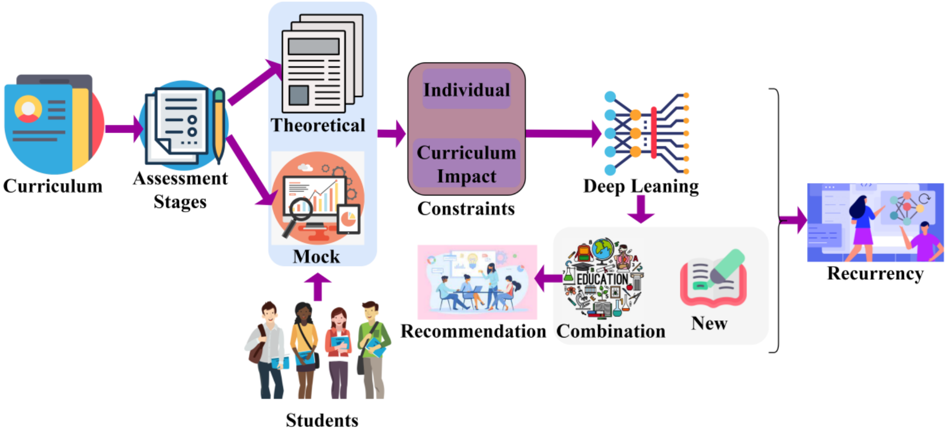

Figure 1: Proposed approach.

Instead, mock practice assessments such as class tests/unit tests/oral tests at any time in which the observed assessment is not important for academic performance amendments. The individual output and curriculum impact reduce the chances of framing different constraints by curriculum impacts. This approach identifies the curriculum impacts as a sequence of curriculum implication or modification or the assessment frequency. The proposed experimental learning assessment approach addresses such curriculum impacts by matching previous student academic performance assessments with current assessments using experimental learning. The first approach consists of curriculum-based knowledge transfer and students' academic performance assessment. Let P^T means the sequence of performance assessment is verified for an individual student in law school at a given time interval such that the student's knowledge $St_k(T)$ to meet the societal factors is expressed as

$$\left.\begin{array}{c} St_k(T) = \left(AP^T * ss^T\right) - c^{Imp} \\ such\,that \\ arg\min_{T} \sum c^{Imp}\ \forall\, AP^T) \end{array}\right\} \tag{1}$$

Equation (1) identifies the causing curriculum impacts E and student skills ss^T at any interval; the objective of minimizing curriculum impacts in all $AP^T \in ss^T$ is estimated. The assessment is verified into two stages (i.e.) theoretical (Th_{AS}) and mock (Mk_{AS}) assessments. This assessment constraint $AS = Th + Mk$ is performed to improve student academic performance such that theoretical assessment is verified between two mock practice assessments and vice-versa. If the number of students in distinct law schools is represented as N^{st} then $Mk = \left(N^{st} \times T\right) - Th$ is the mock practice assessment that is computed for integrated curriculum verification and different sessions. The proposed approach is analyzed using [15] data; a brief discussion of the same is presented later in this article. From the given data, a numerical observation for (Business Finance, music, and web development) for different levels is presented in Table 1.

As presented in Table 1, the Mk_{AS} requires different sessions and levels based on the course. The course requires $St_k(T)$ and N^{st} for meeting the curriculum and financial requirements. Therefore, this data is used for validating the recurrence and modifications. Using the curriculum impact further recommendations and learning implications are facilitated. Let $C(Th)$ and $C(Mk)$ represent the curriculum of AP^T indifferent sessions are computed for N^{st} and c^{Imp} is curriculum impact occurrence identification in all Mk is expressed as

$$C(Th) = N^{st} * Th_{AS} : AP^T, \forall c^{Imp} = 0 \tag{2}$$

$$C(Mk) = \frac{E}{N^{st}} \times Mk_{AS} : ss^T * AP^T, \forall c^{Imp} \neq 0 \tag{3}$$

As per Equations (2) and (3), the curriculum verification is performed for the instances of $(N^{st} \times T)$ and $\left(\frac{c^{Imp}}{N^{st}} \times Mk\right)$ is matched with the student's current academic performance. Now, based on the different sessions and integrated curriculum computation as in Equations (2) and (3), the above Equation (1) is re-written as

$$St_k(T) = C(Th) - C(Mk) = N^{st} * Th_{AS} : \frac{c^{Imp}}{N^{st}} \times Mk_{AS} : ss^T * AP^T \tag{4}$$

	Levels	Th_{AS} *Sessions*	Mk_{AS} *Sessions*	Th_{AS} *Assessment*	Mk_{AS} *Assessment*
	1	*65*	*20*	√	√
	2	*51*	*16*	√	
Course 1	*3*	*69*	*18*	√	
	4	*74*	*29*	√	√
	5	*72*	*44*	√	√
	1	*42*	*10*	√	
	2	*58*	*85*	√	√
Course 2	*3*	*125*	*8*	√	
	4	*187*	*113*	√	√
	5	*224*	*98*	√	
	1	*25*	*109*	√	
	2	*125*	*135*	√	√
Course 3	*3*	*11*	*7*	√	
	4	*157*	*84*	√	
	5	*138*	*120*	√	√

Table 1: Data Observations for Different Studies.

For the above-expanded student knowledge in the curriculum, the sequence of $Mk_{AS} \in T$ is to be before verified before addressing the first mock practices as per Equation (4). This assessment is used to identify the curriculum impact at the time of performing joint analysis using deep learning.

The individual's output and curriculum impact is verified using the available curriculum information with different stages through experimental learning. The student skills and academic performance assessments are improved through conducting multiple mock training and law sessions recurrently. For this sequence, the number of students attending periodical mock training practices is identified based on the instance of $N^{st} \in Mk$ is expressed as

$$N^{st}(Mk) = \left(1 - \frac{Th_{AS}}{N^{st}}\right) Mk_{AS-1} + \sum_{i=1}^{T} \frac{\left(\frac{ss^T + AP^T}{N^{st}}\right)_{i-1} - Mk_{T-1}}{T} \quad (5)$$

Equation (5) follows the law student's academic performance with theoretical and mock training practices for improving student knowledge. The previous student knowledge observation is stored in the curriculum; therefore, the individual student knowledge, skills, academic performance, and curriculum impact are jointly analyzed for performance corrections. Therefore, from the sequence of $St_k(T) = C(Th) - C(Mk)\left[1 - N^{st}(Mk)\right]$ is the individual output without curriculum impact. The joint analysis of $\left(\exists_{Th_{AS}}\right)$ and $\left(\exists_{Mk_{AS}}\right)$ for considering the different assessment stages and their difficulty levels, experimental learning induces multiple assessment constraints. Based on periodical mock training at the initial stage is expressed as

$$\exists_{Th_{AS}} = \left(\frac{C(Th)}{\sum_{i \in T}\left[N^{st}(Mk) * AP^T\right]_i}\right) \quad (6)$$

$$\exists_{Mk_{AS}} = \left(\frac{T\left(C(Th) + C(Mk)\right)}{\sum_{i \in T}(N^{st}(Th))_i \left\{\left(1 - N^{st}(Mk)\right) \times C(Th)\right\}_i}\right) \quad (7)$$

The above Equations (6) and (7) estimate the joint analysis of the curriculum data observed from theoretical and practical knowledge implications and assessments, for instance, at T interval. The stored curriculum data is compared with current curriculum performance to improve student knowledge. The individual assessment and curriculum impact validations using the considered input data from the source are presented in Figure 2.

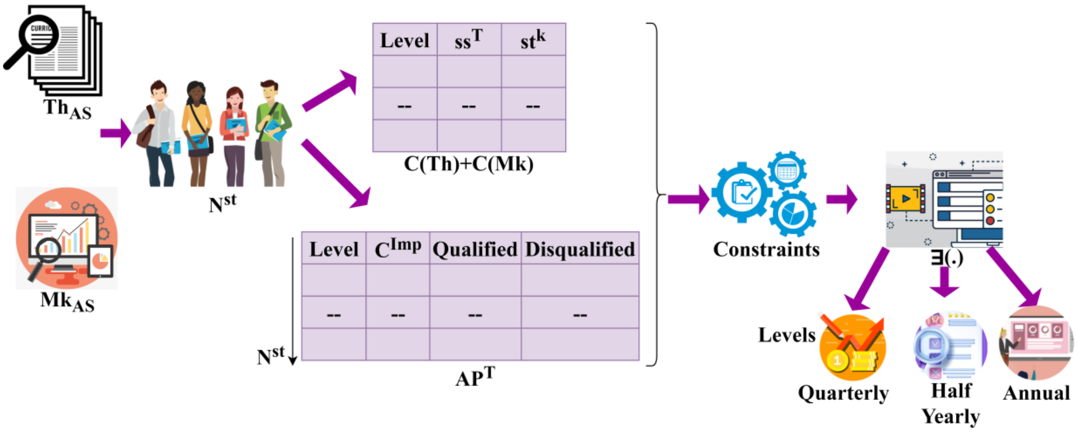

Figure 2: Individual assessment and curriculum impact.

The individual and constraint-based assessment requires differentiated factors for N^{st}. In the individual analysis, $C(Th)$ and $C(Mk)$ are jointly performed to a student for extracting St^k using ss^T. In the AP^T process, qualification ratio determining the performance. The performance of the curriculum over the student qualification shows its impact on analysis. Therefore the constraints are analyzed using deep learning for recommendations and curriculum modifications. The constraints observed from the dataset are discussed later in this article (Figure 2). In this approach, the performance assessment of $\exists_{Th_{AS}}$, $\exists_{Mk_{AS}}$, $C(Th)$ and $C(Mk)$ is the serving inputs for the deep learning paradigm. The periodic performance assessment for curriculum verification helps to identify the impacts in joint analysis relies on the constraint Th_{AS} and $Mk_{AS} \in T$. This deep-learning process is discussed in the following session.

4 DEEP LEARNING PROCESS FOR EXPERIMENTAL ANALYSIS

In the academic performance analysis, deep learning is used to identify the amendments of $\exists_{Th_{AS}}$ or $\exists_{Mk_{AS}}$ and estimating curriculum impacts. The deep learning paradigm depends on already stored student knowledge based on their academic performance; the more accurate curriculum recommendation is achievable. The multiple assessment constraints may vary with performance validation. Therefore, the stored student knowledge and different sessions help to classify assessment stages in both the stages of $N^{st}(Mk)$ for all T sessions. In particular, this deep learning performs two types of approach, namely recurrent assessments for different stages and generating new constraints for improving recommendations. In the recurrent assessment, the theoretical and mock practice assessments are verified to augment the already stored student knowledge of AP^T. Instead, framing new constraints for different stages of observed curriculum data based on AP^T is augmented to improve the $St_k(T)$ along with better academic performance assessment and identification of curriculum impacts.

As per the sequential instance, the recurrent assessment inputs are AP^T and T. The framing of different constraints toward performance assessment of $AP^T \in T$ is combined under theoretical and practical knowledge implications relying on the periodical occurrence in that instance. The specific analysis of this combination is performed for different stages.

In the combined analysis, the academic performance assessments and multiple assessment constraints are analyzed independently for current performance validation. The performance validation is computed for all $N^{st}(Mk)$ and $(N^{st}T)$ the students in law school after which curriculum-based knowledge transfer is used to train the initial knowledge with periodical mock practices and law sessions. The individual output based on performance validation for different sessions $(InO_1 to\, InO_T)$ is evaluated as

$$\left.\begin{array}{c} InO_1 = Th_{AS_1} \\ InO_2 = 2Th_{AS_2} - 2(Mk)_2 - c^{Imp^1} \\ InO_3 = 3Th_{AS_3} - 3(Mk)_3 - c^{Imp^3} \\ \vdots \\ InO_T = N^{st}Th_{AS_T} - N^{st}(Mk)_T - c^{Imp^{T-1}} \end{array}\right\} \tag{8}$$

Such that,

$$\left.\begin{array}{c} Mkt_1 = Th_{AS_1} \\ Mkt_2 = 2(Mk) + C(Th)_1 \\ Mkt_3 = 3(Mk) + C(Mk)_2 - C(Th)_1 \\ \vdots \\ Mkt_T = N^{st}(Mk)_T + C(Mk)_{T-1} - C(Th)_{T-2} \end{array}\right\} \tag{9}$$

The analysis of individual output and curriculum impact frames new constraints based on theoretical and mock practices assessment of individual students from InO_1 to InO_T sequences and mock training sequences from Mkt_1 to Mkt_T. The DL model for individual and curriculum impact based on the constraints is represented in Figure 3

The T is usually segregated as quarterly, half-yearly, and annual as levels (c in the dataset) for $\exists_{Th_{AS}}$ and $\exists_{Mk_{AS}}$. This is performed for N in extracting $InO_1 \; to \, InO_T$ with median $\exists$. The Mk_{AS} is alone different as $N > N^{st}(M_k)$ is possible and therefore t_T is independently extracted. Therefore, InO_T and $t_T \,\forall N^{st}$ is used for combined ss^T and C^{Imp} (Figure 3). Now, the combination is analyzed using knowledge transfer based on the different stages and difficulty levels (occurring instances). The constraint of $T \in InO$ does not equal the constraint $T \in Mkt$ is the combing condition exploited for improving the recommendations. If the assessment of theoretical practices is the initial sequence observation, then Mkt are performed using mock practices. This means the sessions take place as per the norms of theoretical and mock practice sequences. Therefore, $N^{st}(Mk) + C(Mk)_{T-1} - C(Th)_{t-2}$ is the mock training and law session sequence is analyzed for the individual student in law school. In the performance validation, the first approach to serving input is (InO_T, Th) from which (Mkt_T, Mk) is computed using different constraints. In this performance analysis, the comparison of individual output and curriculum impact is verified such that $Th = \{InO_T \cup C(Th)\}$ and $Mk = \{InO_T \cap C(Mk)\}$ is jointly analyzed. The training of the student knowledge is achieved in the first stage, from which the different constraints are combined alone. After the combination process, the curriculum of the individual student is compared with time intervals based on $C(Mk)$ the occurring instance. Here, the inputs are $C(Mk)$ and Mk are the student knowledge improvement serves as the training for all the students exploited under Mk. First, the recommendation is designed using deep learning. Based on the recommendations, if the mock training practices are conducted to improve student knowledge and skills and AP^T. If AP^T and curriculum impact at T interval (i.e.) if $\exists_{Th_{AS}} < \exists_{Mk_{AS}}$ is observed whereas $\exists_{Th_{AS}} > \exists_{Mk_{AS}}$ is true, then the recurrent assessments for different stages are performed from the individual output. The new constraint for mock training practices is further analyzed and combined under Mkt_T, where $T \in Th$ is achieved. The performance validation based on the data provided in Table 1 is presented in Table 2. The performance based on N^{st} retention is considered for the validation of ss^T and C^{Imp}.

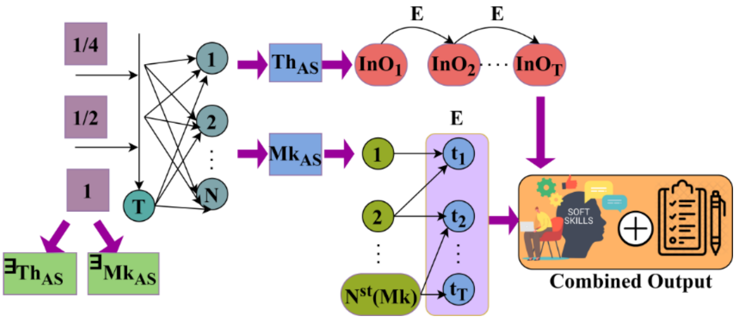

Figure 3: DL model for AP^T.

	Levels	Th_{AS} Assessment	Qualified	Mk_{AS} Assessment	Qualified	ss^T	C^{Imp}
Course 1	1	3	8014	5694	78.963	3.8	5.23
	2	2	7884	4919	77.69	3.6	4.22
	3	4	7982	5987	78.648	3.8	4.39
	4	5	8265	6358	81.437	4.1	5.9
	5	1	8523	7236	83.978	4.5	6.58
Course 2	1	2	8045	8095	79.269	4.3	4.89
	2	3	7963	7845	78.461	3.9	5.26
	3	5	8536	6536	84.107	6.3	6.89
	4	4	8769	6874	86.403	6.9	7.01
	5	8	8847	7012	87.172	6.1	7.2
Course 3	1	6	8459	8095	83.349	5.8	6.15
	2	4	8745	7896	86.167	6.5	7.45
	3	8	8991	6987	88.591	7.2	7.61
	4	10	8745	5478	86.167	6.5	7.45
	5	9	8564	5264	84.383	6.3	6.98

Table 2: Performance Based on N^{st}.

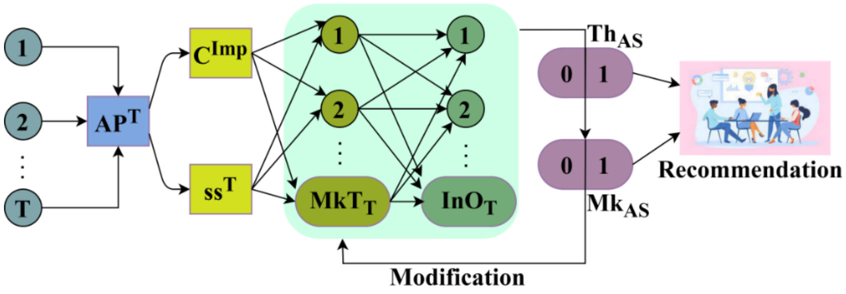

Figure 4: DL model-based on C^{Imp}.

Based on the performance validation, the constraint $\exists_{Th_{AS}} > \exists_{Mk_{AS}}$ outputs in "1" and instead $\exists_{Th_{AS}} < \exists_{Mk_{AS}}$ outputs in "0". If 0 is identified for the sequence, then mock practices are recommended. Hence, the recommendation of any Th in Mk based on individual output and curriculum impact as per Equations (8) and (9). Here, the academic performance validation must be verified by the deep learning paradigm, which trains the student's knowledge with societal factors (Table 2).

In the deep learning process, T serves as the joint analysis for recommendation with the mock practices of AP^T is validated. In the curriculum-based knowledge transfer, (MkT_T, Mk) is achieved for precise recommendations to verify academic performance and if there is any curriculum impact occurred. If Mk occurs, then c^{Imp} is computed for improving performance corrections. Instead, based on the constraint $\exists_{Mk_{AS}}$, the mock training practice is recommended. Here, the individual output and mock training vary from the combined analysis as illustrated using Equations (10) and (11) is expressed ad

$$\left.\begin{array}{c} InO_1 = 0 \\ InO_2 = C(Th)_1 + 2Mk_{AS_1} - c^{Imp^1} \\ InO_3 = C(Th)_2 + 3Mk_{AS_3} - c^{Imp^2} \\ \vdots \\ InO_T = C(Th)_{T-1} + Mk_{AS_{T-2}} - c^{Imp^{T-1}} \end{array}\right\} \quad (10)$$

Equation (10) represents the occurrence of theoretical assessment for different sessions and the curriculum impact occurrence in law school student performance validation. Based on the theoretical and practical assessment outputs in $InO_1 = 0$ is the previous individual output observed from the different sessions and mock training. Where the training for Mk is output in zero. Therefore, the different stages are not considered in the combined analysis. In both the analysis, the curriculum impact increases before which the curriculum-based knowledge transfer improves as

$$\left.\begin{aligned} MkT_1 &= \frac{1\left(Mk_{AS_1}\right)+Th_{AS-1}}{N^{st}} \\ MkT_2 &= \frac{2\left(Mk_{AS_2}\right)+Th_{AS-2}}{N^{st}} - C\left(Mk\right)_1 \\ MkT_3 &= \frac{3\left(Mk_{AS_3}\right)+Th_{AS-3}}{N^{st}} - C\left(Mk\right)_2 \\ &\vdots \\ MkT_T &= \frac{t\left(t_{d_t}\right)+Th_{AS-T}}{N^{st}} - C\left(Mk\right)_{T-1} \end{aligned}\right\} \quad (11)$$

The curriculum knowledge of law students is trained based on academic performance and theoretical assessments at the end of all mock practices. The final DL model for curriculum-based knowledge transfer is presented in Figure 4.

The C^{Imp} over the curriculum and N^{st} is analyzed using the final DL phases. Considering the C^{Imp} and ss^T over the MkT_T and InO_T, the output is either $o/1$ for Th_{AS} and Mk_{AS}. Therefore the occurrences of $InO_T = 0$ (or) $MkT_T = 0$ requires training based on the modification granted. If both assessments provide the maximum result, then the recommendation is preceded (Figure 4). In the knowledge improvement training, based on theoretical and practical assessments, each student is identified for performance amendments. In this proposed approach, if curriculum impact and mock training are not performed, for instance, then the whole class of $St_k(T)$ will be combined under $c^{Imp}.Mk$ resulting in a better recommendation.

5 DISCUSSION

The discussion section presents the analysis using the "Udemy Courses" dataset [15]. This dataset contains 12 fields accommodating the sessions, fees, difficulty levels, etc., of three different courses. A total of 3679 data inputs classified under three courses are used for analysis. Based on the available data, the course and reviews are used for framing constraints (discussed under Figure 2). A sample set of constraints is presented in Table 3 with the Th_{AS} and Mk_{AS} requirement.

The constraints listed in Table 3 are extracted based on the reviews from the accounted dataset. The constraints are satisfied with the appropriate solutions. The academic curriculum impact over ss^T is the prominent factor for constraint modification or satisfaction. If a constraint remains unsatisfied, then modification is recommended. Therefore the new assessment of C^{Imp} is performed for Th_{AS} and Mk_{AS} across multiple new constraints (Table 3). Now the analysis for C^{Imp} and ss^T based on varying $(T = 15)$ is presented in Figure 5.

No.	*Constraints*	Th_{AS} *Levels*	Mk_{AS} *Levels*	*Frequency*
1	*Number of Levels*	*2*	*1*	*Q*
2	*Maximum possible admissions*	*1*	*0*	*A*
3	*Student assignment*	*3*	*2*	*A*
4	*Qualifying Rate*	*4*	*2*	*Q*
5	*Disqualification Reason*	*3*	*1*	*Q*
6	*Staff Assessment*	*2*	*1*	*H*
7	*Teaching Quality Improvements*	*4*	*3*	*Q*

8	*Student to Teacher Ratio*	*1*	*0*	*Q*
9	*Skill Development Programs*	*5*	*4*	*H*
10	*Infrastructure Utilities*	*4*	*2*	*A*
11	*Practical Sessions*	*5*	*3*	*Q*

Table 3: Sample Constraints.

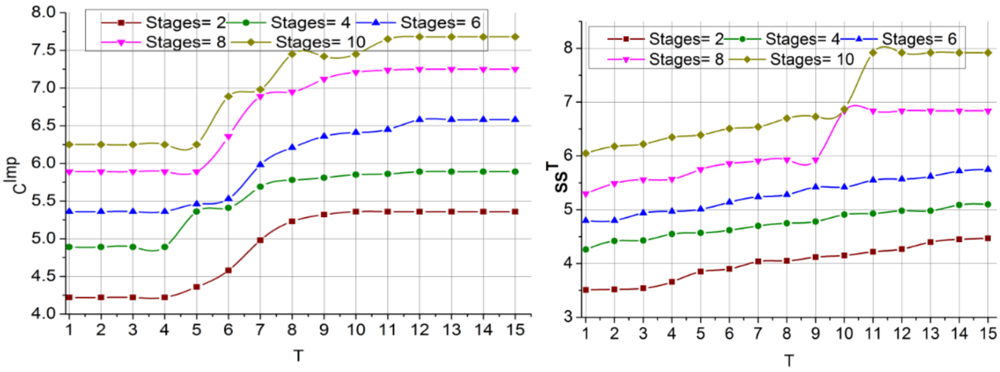

Figure 5: C^{Imp} and ss^T analysis.

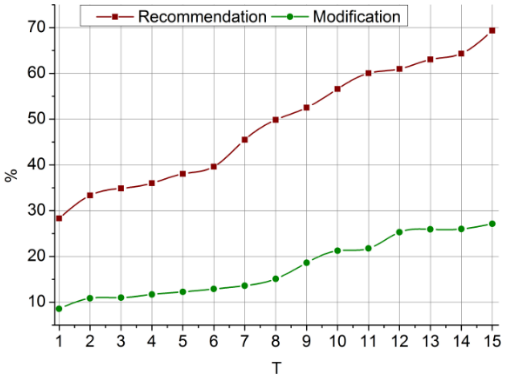

Figure 6: Modification and recommendation analysis.

The varying T requires DL instances as in Equations (8) and (9) or a modified form as in Equations (10) and (11). Based on the t_T that is individually performed in $InO_T \forall N^{st}(Mk)$, the ss^T is extracted. Contrarily, the E between successive $InO_1 \, to \, InO_T$ requires $\exists_{ThAS} + \exists_{Mk_{AS}}$ for identifying the precise C^{Imp}. This is therefore required across various evaluation stages per annum. Therefore the previous changes are referred to for identifying 0 or 1 across Mk_{T_T} and InO_T combinations. This maximizes the ss^T assessment and C^{Imp}. Based on these two assessments, the modifications and recommendations towards the curriculum implication are analyzed in Figure 6.

The various levels/ stages of assessment require InO_1 to InO_T for improving recommendations. The recommendations are implied for the curriculum assessed N^{st}. From this assessment, $\exists_{Th_{AS}}$ and $\exists_{Mk_{AS}}$ frequencies are identified. Depending on the joint $ss^T \oplus C^I mp$, the recommendations for the $N \in Th_{AS}$ and Mk_{AS} is provided. Similarly the t_T demand increases the chances for high than the modification in the assessment model. Therefore the recommendations are high than the modifications (Refer to Figure 6).

6 COMPARATIVE ANALYSIS SECTION

The comparative analysis section presents the proposed approach's validation using external methods and metrics. The metrics include recommendation ratio, modifications, assessment constraints, processing time, and assessment rate. The session per year and the stages are varied for 60 and 10, respectively. In this comparative analysis, the methods CPN-SFA [20], TCM [13], and BLSTM+CRF [29] from the related works section are considered.

6.1 Recommendation Ratio

In Figure 7, the student skills and assessments are processed based on performing mock training and law sessions for different stages are carried out for improving performance amendments. The theoretical and mock practice assessment is computed for integrated curriculum verification and different sessions using student academic performance assessment. The individual output and curriculum impact is computed to satisfy both the constraints $\left(N^{st} \times T\right)$ and $\left(\frac{c^{Imp}}{N^{st}} \times Mk\right)$ in law school curriculum analysis. This causing curriculum impact is identified by the deep learning process with $arg \min_T \sum c^{Imp} \forall AP^T$ such that the performance assessment achieves successive recommendations for the curriculum analysis sequences. Therefore, the further different stages and difficulty levels are identified in the law school curriculum for making a better recommendation. Based on this, theoretical and mock practice assessment satisfies a high recommendation ratio for mock training and framing new constraints rely on theoretical and practical knowledge implications in training; the processing time is reduced and the increased recommendation ratio is due to multiple assessment constraints.

6.2 Modifications

In Figure 8, law school students' curriculum-based knowledge transfer and performance assessment are verified for recommending theoretical and practical sessions for different stages to improve their knowledge and performance. The combination process is performed for framing new constraints using a deep learning process for identifying the individual output and curriculum impact at the time of curriculum recommendation. The modifications and processing time is computed for performing students' skills and assessments through the experimental learning process at different time intervals. The assessment frequency or modifications in student assessment based on their knowledge and skill in learning is identified from the first stage. The multiple assessment constraints may vary with performance validation. Therefore, the stored student knowledge and multiple sessions help to classify assessment stages in different stages, satisfies $N^{st}\left(Mk\right)$ for all T. This proposed approach for improving student academic performance, preventing curriculum impact and processing time. The academic performance assessment is performed based on different sessions and curriculum verification followed by the individual output for which the proposed approach satisfies less modification.

6.3 Assessment Constraints

In Figure 9, the multiple assessment constraints induce different stages and difficulty in theoretical and practical knowledge implications, and assessment for individual or multiple students in law school requires different stages for improving academic performance. The recurrent assessment is exploited for different stages and framing new constraints by inducing multiple assessment constraints, and the assessment rate is computed for identifying curriculum impacts. Based on the performance assessment of law students from different stages, some impacts and modifications occurred, and that occurrence is identified using deep learning for improving the recommendations. The integrated curriculum verification does not require different sessions and curriculum impact and then the new constraint is generated through the learning process for improving student knowledge. The modification in student academic performance is addressed for preventing curriculum impact and recommending mock practices and law sessions to improve the performance. High assessment constraint is ensured if curriculum implication is observed in this proposed approach. The curriculum input for deep learning recommendation, along with different stages, in which the proposed approach achieves fewer assessment constraints in that session.

6.4 Processing Time

The individual student skill and performance assessments in law school are analyzed for ease of framing different constraints using deep learning, as illustrated in Figure 10. In this approach, the recurrent assessments for different stages and new constraints satisfy less processing time by identifying individual output, and curriculum impacts through the experimental learning process for periodical training instances rely on different stages. In this approach, the theoretical and mock assessments are computed to improve student knowledge. The joint analysis of $\left(\exists_{Th_{AS}}\right)$ and $\left(\exists_{Mk_{AS}}\right)$ is considered the different assessment stages and their difficulty levels in the experimental learning are identified through periodical mock training and law sessions. The modification or curriculum implication in students' academic performance assessments is identified for satisfying the condition $St_k\left(T\right)=C\left(Th\right)-C\left(Mk\right)\left[1-N^{st}\left(Mk\right)\right]$. This condition is used for computing individual output without any curriculum impact occurrence, preventing processing time. Deep learning identifies assessment constraints and modifications are mitigated for student knowledge implication. Based on the performance validation, the processing time is estimated.

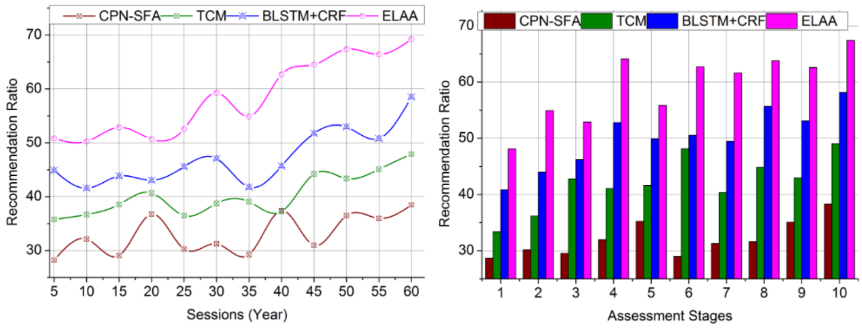

Figure 7: Recommendation ratio.

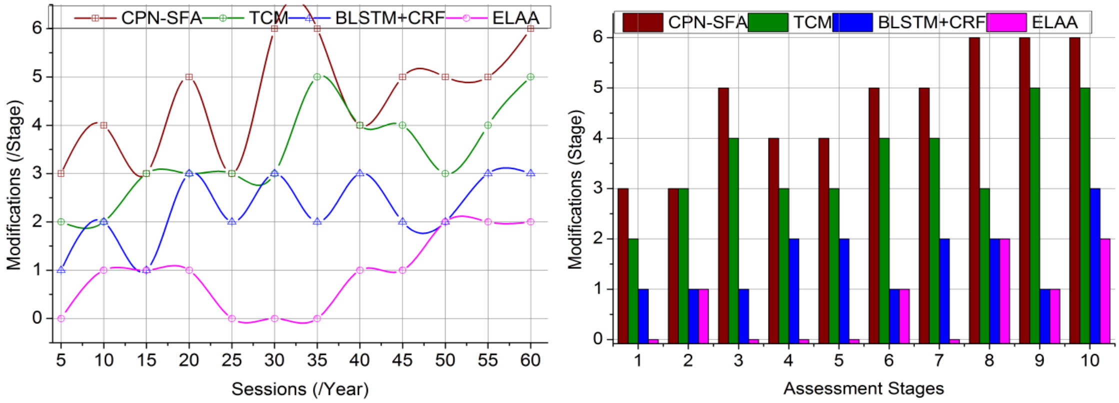

Figure 8: Modifications.

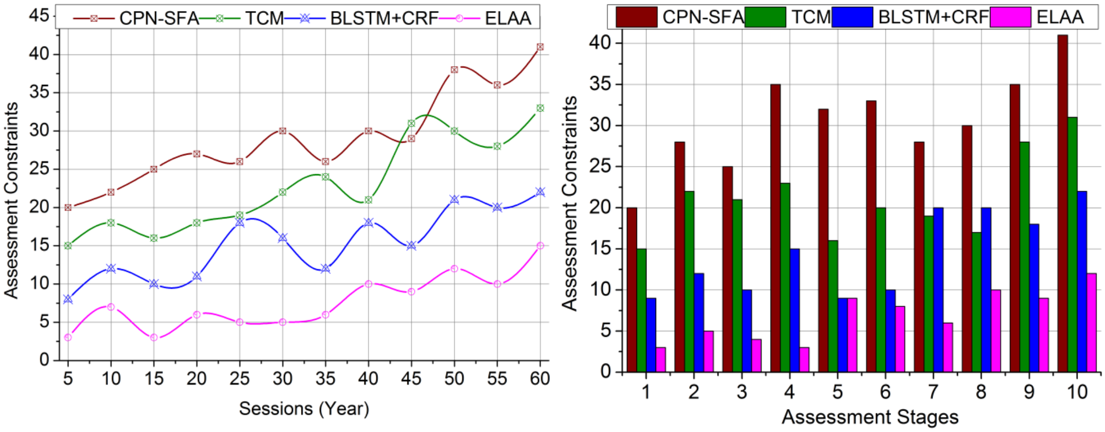

Figure 9: Assessment constraints.

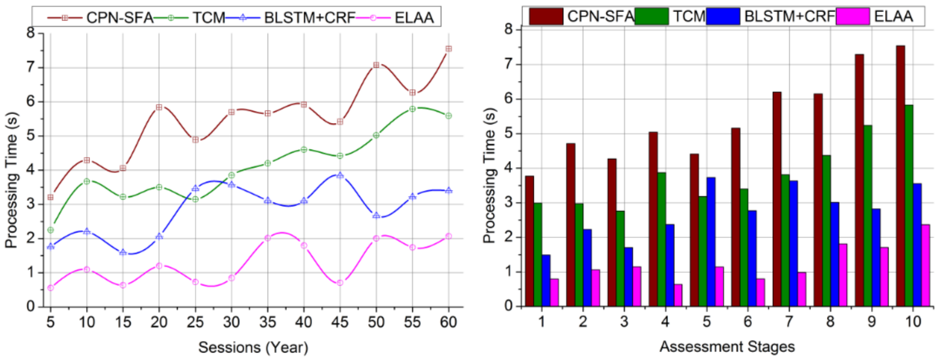

Figure 10: Processing time.

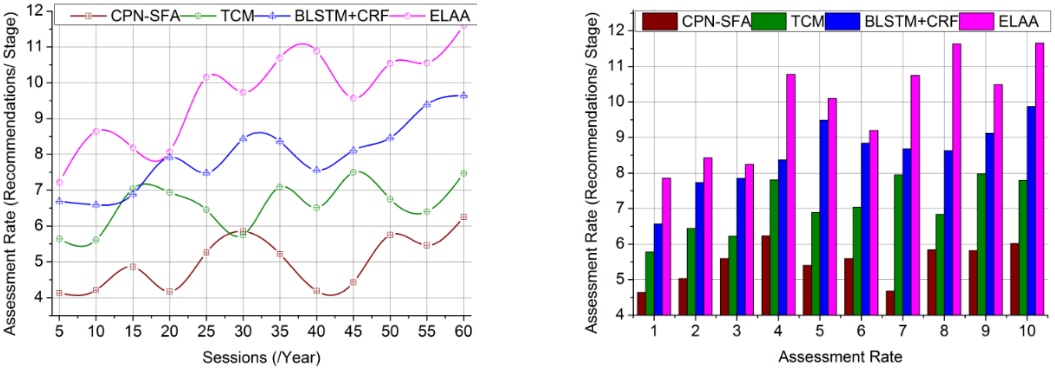

Figure 11: Assessment rate.

Metrics	CPN-SFA	TCM	BLSTM+CRF	ELAA
Recommendation Ratio	*38.46*	*47.91*	*58.51*	*69.247*
Modifications (/Stage)	*6*	*5*	*3*	*2*
Assessment Constraints	*41*	*33*	*22*	*15*
Processing Time (s)	*7.55*	*5.59*	*3.41*	*2.067*
Assessment Rate (Recommendations/Stage)	*6.25*	*7.47*	*9.64*	*11.599*

Table 4: Comparison Summary for Sessions.

Summary: The proposed approach improves the recommendation ratio and assessment rate by 10.48% and 10.96%, respectively. This approach reduces modifications, assessment constraints, and processing time by 9.52%, 8.85%, and 10.42%, respectively.

Metrics	CPN-SFA	TCM	BLSTM+CRF	ELAA
Recommendation Ratio	*38.31*	*49.06*	*58.14*	*67.406*
Modifications (/Stage)	*6*	*5*	*3*	*2*
Assessment Constraints	*41*	*31*	*22*	*12*
Processing Time (s)	*7.54*	*5.83*	*3.55*	*2.364*
Assessment Rate (Recommendations/Stage)	*6.02*	*7.81*	*9.87*	*11.658*

Table 5: Comparison Summary for Assessment Rate.

Summary: The proposed approach improves the recommendation ratio and assessment rate by 9.45% and 10.75%, respectively. This approach reduces modifications, assessment constraints, and processing time by 9.52%, 10.29%, and 9.68%, respectively.

6.5 Assessment Rate

The assessment rate is high in this proposed experimental learning assessment approach for law school students' academic performance validation using different sessions and integrated curriculum verification (Refer to Figure 11). Based on the individual output and curriculum impact assessment from law school curriculum is computed for different stages for improving the recommendations. In this manuscript, the curriculum data observed from the entire student in law school is estimated for ease of providing mock training and law sessions for different stages. The curriculum-based knowledge transfer and performance assessment are handled to meet the societal factors using experimental learning for increasing the theoretical and mock sessions for academic performance amendments [as per Equations (6) and (7)]. The student skills and assessments are analyzed to improve curriculum recommendations through student performance validation. In this proposed approach, the individual student's theoretical and practical knowledge implications and assessments are jointly analyzed through deep learning for better performance. From the different stages and curriculum data analysis, different sessions are recommended for each student, such as periodically analyzing student performance. In this approach, the student academic performance relies on students attending mock training and law sessions, and therefore, the individual output achieves a high assessment rate. Tables 4 and 5 present the summary of the comparisons for the sessions and assessment rate, respectively.

7 CONCLUSION

This article introduced an experimental learning assessment approach for improving the students' skills and academic performance validation. In assessing the student's performance, the theoretical and mock sessions are utilized based on students' skills and constraints. The performance assessment is periodically using the curriculum impact and student knowledge. In this assessment process, deep learning is induced across multiple constraints. Student differentiation for various mock training and curriculum assessment are considered in the validation process. The learning instances are trained across different stages and constraints for preventing modifications. The modifications are prevented from admitting validation across different recommendations. The combined recommendations and modifications are utilized in the recurrent learning process to prevent varying assessment constraints. This constraint suppression is performed using a modified curriculum and recommendation-based skill identification. Therefore the proposed approach improves the recommendation ratio and assessment rate by 9.45% and 10.75%, respectively. This approach reduces modifications, assessment constraints, and processing time by 9.52%, 10.29%, and 9.68%, respectively.

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