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Sequence Aware Representation Learning Traces Evolving Teaching Practices Through Historical Curriculum Records

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Abstract

The continuous process of curriculum change plays an important role in making sure that the curriculum stays of high quality and promotes competency-based learning while also taking into consideration the needs of the ever-changing workforce. Traditional methods of curriculum analysis usually consider each version of the curriculum separately and are unable to incorporate the relation of curriculum versions to changes over time. This limitation hinders their ability to identify any changes in the way the instruction or material delivery has been changed. In order to solve this problem, in this paper, a novel Sequence-Aware Representation Learning (SARL) model for tracking the evolution of teaching practices using historical curriculum data of higher education institutions in Uzbekistan is introduced. The proposed SARL model considers curriculum revisions as a sequence of events and connects them to several aspects of education, such as the structure of the course, learning outcome, assessment, relationship of prerequisites, and credits, using the unified feature representation. The use of learned representations will help analyze the way the curriculum is being changed and detect any changes in the instruction as a valuable basis for decision-making regarding curriculum planning and educational policies. The framework has been verified using the curriculum history dataset collected from the universities of Uzbekistan, in comparison with such approaches as Logistic Regression, Random Forest, LSTM, and Bi-LSTM. According to the results of the experiments, the proposed SARL framework proved to be effective with the following metrics in terms of accuracy (96.84 %), precision (96.41 %), recall (96.12 %), F1 score (96.26 %), and AUC (97.31 %). Furthermore, the framework detected 96.85% of curriculum changes, 96.43% of teaching practices, 97.18% of sequence consistencies, and 96.79% of curriculum evolution predictions, demonstrating the effectiveness in capturing long-term trends of instruction changes.

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Introduction

Higher education is continuously evolving to meet new educational requirements, the advancement in technology, and the needs of the industry. Universities continuously revise their course structure every year by changing their course content and objective, mode of teaching, assessment, and prerequisites. Over time, universities are continuously revising the courses by changing the course content, the learning outcomes, the teaching strategy, the assessment system, and the prerequisite structure (Molontay et al., 2020). These continuous revisions collectively create valuable historical curriculum records that document the evolution of teaching practices, instructional strategies, and curriculum structures over time (Herbst, 2002). Such records will help in understanding the past curriculum changes, designing future curriculums, and maintaining quality in education. Analysis of important patterns from the curriculum changes over time, however, is not an easy process since such changes occur over many academic years. With the introduction of more and more digital academic management systems in the universities, the storage space for such data is increasing. Following are some of the items which may be included in the records: Course descriptions, credits, learning outcomes, assessment, and curriculum revisions. This data can be used for analyzing how the practices of the teacher evolve over time (Huang et al., 2020; Little, 2003).

However, the vast majority of the contemporary techniques of curriculum analysis analyze each particular version of a curriculum separately without taking into account the connection between the previous and the following ones; thus, it is impossible to describe the process of changing in detail (Hooshyar et al., 2026). In recent years, there have been numerous changes in the curricula of higher education institutions in Uzbekistan, which were carried out with an aim to improve the quality of education, develop digital learning and introduce higher education programs in accordance with the international standards (Yang et al., 2025).

In view of the increasing number of curriculum modifications, there is a growing necessity for intelligent solutions for analyzing previous curricula records and supporting academic decision making (Kim, 2025). The analysis of educational data was performed using traditional statistical and machine learning techniques that assume each curriculum record as an independent sample (Wang, 2026). Such techniques cannot account for the sequentially of curriculum modifications; therefore, tracking long-term teaching trends and curriculum evolution becomes difficult. Hence, there is a necessity to develop such learning algorithms that would be able to learn from the temporal sequence of curriculum changes while preserving relations between different segments of the curriculum (Jung et al., 2021; Zhu et al., 2021).

Sequence-aware representation learning has proven to be an effective technique in sequential data modeling. Rather than analyzing records separately, it will take into consideration the order and context of the historic information (Cai et al., 2024). In the case of curriculum records, it will be able to identify the changes that happen to the courses each year in relation to the curriculum, learning objectives, assessment, and instruction (Lyu et al., 2022). The representation learning provides more insight on curriculum development and makes future curriculum changes predictable (Tetzlaff et al., 2021; Zhang et al., 2017; Duschl et al., 2011).

Key Contributions of the Research

- Sequence-Aware Curriculum Modeling: This study proposes a Sequence-Aware Representation Learning (SARL) framework that models historical curriculum records as sequential data to capture the evolution of teaching practices over multiple academic years.
- Educational Representation: The suggested approach considers the structure of courses, learning objectives, methods of assessment, allocation of credits, and prerequisite information to create an educational representation.
- Decision Making in Higher Education of Uzbekistan: The suggested model is able to discover the patterns of curriculum evolution and provide useful insights for making curriculum-related decisions in Uzbekistan universities.

Organization of the remaining sections of the paper is as follows. Section II presents an overview of the literature on curriculum analytics, representation learning, and educational data mining. Section III introduces Sequence-Aware Representation Learning (SARL) framework for modeling historical curriculum data and detecting changes in pedagogy practices. Section IV describes the experiment design, evaluation, and comparison results. The discussion

of the results and benefits of the proposed approach is presented in Section V. Finally, the conclusions are drawn in Section VI.

Literature Review

Lebis et al., (2024) proposed an approach for full individualized curriculum planning, which involves consideration of student knowledge decay and creation of individualized learning paths. It was found out that the process of forgetting influences curriculum optimization to a great extent, and it emphasized the generation of adaptive curricula instead of rigid curricula. An attempt has been made to develop an educational planning approach that will incorporate time-based learning characteristics in order to improve personalized education planning. However, the study was mainly focused on the issue of learner-centered curriculum generation, not on the historical revision of curricula to determine their evolution.

The study by Deng et al., (2023) introduced the knowledge-aware Modeling framework for Online Course Recommendation, successfully integrating the Knowledge graph and deep learning models. The introduced model relied on graph embeddings to represent diverse course information and sequence learning for modeling dynamic learner interest. Experimental studies proved that the recommendations generated by the model are highly accurate compared to existing recommendation models. Although the methodology could be effectively used for modeling sequential behavior in education, it focused only on the investigation of personalized course recommendations and did not address the problem of the temporal evolution of curriculums and pedagogical practices over different academic periods.

Liu et al., (2024), Curriculum versioning has also been extensively investigated with respect to the viewpoint of document evolution and semantic change analysis. In contrast to student-based educational data analytics, the document version analysis approach views curriculum evolution in terms of evolving structured documents where changes in the descriptions of courses, learning outcomes, prerequisites, and assessment policies are recorded throughout different periods of education. The temporal representation of the documents allows educational organizations to detect the trends of curriculum evolution, the changes in the educational policies and changes in pedagogical approaches while maintaining temporal dependencies among consecutive curriculum versions. Yet, the majority of existing document evolution techniques have been developed for general textual and software documentation purposes.

Abu-Salih & Alotaibi, (2024) New advances in educational knowledge graphs and ontology-based curricula modeling have shown that the representation of curriculum components as semantic entities is of great importance. The usage of the knowledge graph technique allows us to describe connections between courses, competencies, learning outcomes, pre-requisites and methods of assessment. However, existing approaches based on the ontology generally offer static semantic descriptions and seldom use temporal sequence learning for analysis of the dynamics of curriculum structures for several academic years.

Zhu et al., (2024) introduced a multi-level denoising model of the sequence by using contrastive learning across cross-signals in sequential recommendation. They suggested a target-driven interest extraction, sequence denoising, and curriculum learning-based approach to improve the representation of the sequence. As per the experiment results, these models have proven themselves very successful compared to other existing recommendation models. The problem of sequential dependencies has been solved; however, the approach has been implemented in the recommendation system and not in curriculum analysis and educational practices in institutions of higher learning.

Temporal representation learning has recently emerged as an effective approach for modeling sequential document evolution. Sequence encoders, temporal embeddings, and contextual representation learning preserve dependencies among historical document revisions and enable prediction of future document states. Although these methods have achieved promising results in temporal knowledge graphs, sequential recommendation, and evolving document repositories, their application to historical curriculum records remains limited. Integrating temporal representation learning with curriculum analytics provides an opportunity to automatically discover evolving teaching practices while maintaining the chronological relationships among curriculum revisions.

Table 1: Comparative Summary of Recent Studies on Sequence-Aware Learning and Historical Curriculum Analysis

Author et al.	Objective	Method/Approach	Key Outcome	Limitation
Lebis et al., (2024)	Personalized curriculum planning	Individualized curriculum generation considering knowledge decay	Improved adaptive learning pathways by modeling temporal forgetting behavior.	Does not analyze historical curriculum evolution or institutional teaching practice changes.
Deng et al., (2023)	Online course recommendation	Knowledge graph embedding with sequence-aware deep learning	Achieved higher recommendation accuracy by capturing learners' sequential interests.	Focused only on course recommendation rather than long-term curriculum evolution.
Liu et al., (2024)	Personalized curriculum planning	Adaptive curriculum generation	No institutional curriculum evolution	Limited to knowledge graph learning without educational curriculum analytics.
Abu-Salih & Alotaibi, (2024)	Review of knowledge graph applications in education	Systematic literature review	Highlighted the benefits of knowledge graphs for curriculum design, learning support, and educational recommendations.	Identified the lack of sequence-aware models for analyzing historical curriculum records.
Zhu et al., (2024)	Sequential recommendation	Multi-level sequence denoising with contrastive learning	Improved sequential representation learning and recommendation performance.	Designed for recommendation tasks and not for tracing evolving teaching practices.

Table 1 demonstrates that existing studies primarily focus on personalized learning, student recommendation systems, knowledge tracing, or static educational knowledge graphs. Although sequence learning and representation learning have been widely investigated, very limited research addresses the temporal evolution of institutional curriculum documents across multiple academic years. Furthermore, existing curriculum analytics methods generally analyze individual curriculum versions independently without modeling semantic relationships between successive revisions. There is also a lack of unified representation learning frameworks capable of jointly encoding course structures, learning outcomes, assessment strategies, prerequisite dependencies, and credit allocations within a temporal learning framework. To bridge these research gaps, this study proposes a Sequence-Aware Representation Learning (SARL) framework that learns chronological curriculum representations from historical curriculum records and supports intelligent curriculum evolution analysis for higher education institutions.

Methodology

Historical Curriculum Data Collection and Preprocessing

Uzbekistan Higher education institutions were taken as samples, and historical curricula data were collected over several years, including course structure, learning outcomes, credit distribution, prerequisites, assessment techniques, and information about the courses for each semester. The initial step for cleaning the collected data was the elimination of duplicate data entries, the treatment of missing data values, and normalization of the format of attributes. Curriculum description texts were tokenized and normed, categorical attributes were coded to numerical attributes, and continuous attributes were normed. Finally, all curriculum revisions were arranged chronologically and transformed into fixed-length feature vectors comprising encoded representations of course structure, learning outcomes, assessment methods, prerequisite relationships, credit allocation, and textual curriculum descriptions. Each curriculum revision was represented by a 256-dimensional feature vector, which served as the input to the proposed Sequence-Aware Representation Learning (SARL) framework. In this preprocessing step, sequential data with high quality are utilized to help learn the curriculum evolution pattern.

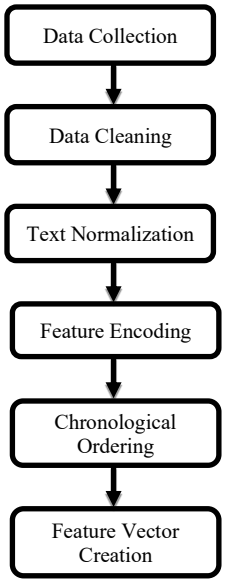


Fig. 1: Workflow of Historical Curriculum Data Preprocessing and Feature Vector Generation

The suggested Sequence-Aware Representation Learning (SARL) framework is based on the procedure demonstrated in fig. 1. The initial step is data collection that implies historical data collection on curricula offered by the higher educational institutions in Uzbekistan. Afterward, collected data is cleansed of duplicate, inconsistent and incomplete data to provide data cleansing. Finally, in sequence, it normalizes the descriptions of curricula by means of tokenization and formatting and then transforms categorical representation of attributes of curricula to numerical representation of attributes (feature encoding). Next, processed records of curricula are arranged in chronological order to preserve the sequence of curriculum changes. Finally, ordered records are transformed to feature vectors, incorporating structure of courses, learning outcomes, methods of assessment, pre-requisites and credits. Those are vectors of features used as an input for the suggested SARL framework to learn temporal representation of curricula and trace evolution of teaching practices.

Prediction Task Definition

The proposed Sequence-Aware Representation Learning (SARL) framework is formulated as a supervised binary classification task for curriculum evolution analysis. Each input sequence consists of curriculum revisions from consecutive academic years, represented by course structure, learning outcomes, assessment methods, prerequisite relationships, and credit allocation. The prediction objective is to determine whether a curriculum revision corresponds to a significant teaching practice evolution (Class = 1) or a routine curriculum update (Class = 0). Significant curriculum evolution refers to substantial modifications affecting pedagogical practices, including changes in learning outcomes, assessment strategies, prerequisite structures, course organization, or credit allocation, whereas routine updates include administrative or formatting revisions without meaningful instructional changes. Therefore, the reported Accuracy, Precision, Recall, F1-score, and AUC measure the capability of the SARL framework to correctly classify curriculum evolution events.

Ground Truth Label Generation

Ground-truth labels were generated by comparing consecutive curriculum versions and identifying meaningful pedagogical changes based on predefined curriculum revision criteria. Each curriculum revision was evaluated using five educational attributes: (i) course structure, (ii) learning outcomes, (iii) assessment methods, (iv) prerequisite relationships, and (v) credit allocation. Curriculum revisions exhibiting substantial modifications in one or more of these attributes were assigned a positive label (Class = 1), while revisions containing only minor administrative or formatting updates were assigned a negative label (Class = 0). These labeled curriculum evolution records were subsequently used for supervised training and evaluation of the proposed SARL framework.

Proposed Sequence-Aware Representation Learning Framework

The SARL framework attempts to model historical curriculum records as a temporal sequence, thus considering the change in teaching practice within different academic years. In the first phase of representation learning for each curriculum feature vector, it is transformed into dense vectors according to the collected information from the course

structure, the set of learning outcomes, assessment methods, prerequisite relations, and credit distribution. A sequence encoder then operates on the sequential representations that learn the contextual relationships between revisions in a sequence. The learned representations are then fed into the prediction layer to identify the curriculum evolution pattern and capture the changes in teaching practice. The model is trained by cross-entropy loss using the Adam Optimizer, and the dropout regularization technique is applied. The suggested framework enables the right determination of the direction of the curriculum evolution and provides an educational planning based on evidence for the higher education institutions in Uzbekistan due to keeping the chronological relations between the curriculum revisions.

Curriculum Feature Representation

$$xt = [ct, lt, at, pt, crt] \quad (1)$$

In this equation (1) is the feature vector of the curriculum information for each year. The feature vector incorporates all the relevant parts of an education, such as the course organization, learning objectives, assessment techniques, prerequisites, and credits. This feature vector will be the input to the Sequence-Aware Representation Learning model and will enable the model to handle the changes in the curriculum in a consistent manner.

Sequence Representation Learning

$$ht = f(xt, ht - 1) \quad (2)$$

Equation (2) depicts how the presented model acquires knowledge about the evolution of curriculum by utilizing the features of the present curriculum as well as the data that can be extracted from the previous year's representation of the curriculum. The sequential learning process not only captures the recent changes in the curriculum but also changes in the teaching practice that have occurred in the past. Therefore, the resultant representation maintains the history of the changes made in the curriculum.

Proposed Sequence-Aware Representation

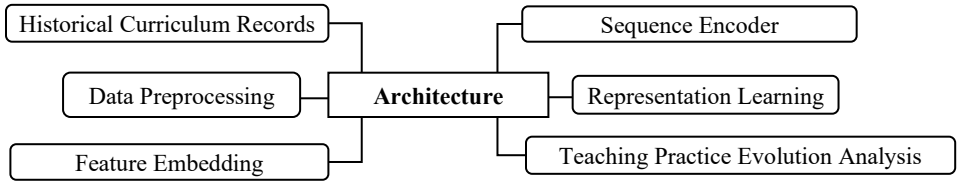


Fig. 2: Proposed Sequence-Aware Representation Learning (SARL) Framework for Tracing Evolving Teaching Practices

Fig. 2 illustrates the general SARL architecture. First, the curriculum history records of Uzbekistan's higher education institutions are gathered, and the data is then preprocessed by removing inaccuracies, normalizing the data, and organizing the information chronologically. Further, the processed data is converted into feature embeddings including course structure, learning outcomes, assessment methods, prerequisite structures, and credits. These embeddings are then sent to the sequence encoder, which learns the relationship between consecutive curriculum revisions and generates meaningful representations using the representation learning module. Lastly, the generated representations are used for analyzing the evolution of teaching practice and identifying the long-term changes in the curriculum, trends in teaching, and evidence-based curriculum planning in higher education.

Although LSTM and Bi-LSTM effectively model temporal dependencies, they primarily focus on sequential hidden-state propagation without explicitly modeling interactions among heterogeneous curriculum attributes. In contrast, the proposed SARL framework introduces an adaptive context fusion mechanism that jointly encodes temporal evolution and semantic curriculum relationships before generating the final latent representation. This enables SARL to preserve long-term curriculum evolution while emphasizing meaningful curriculum revisions, resulting in richer educational representations for curriculum evolution prediction.

Experimental Results

Experimental Setup, Dataset, and Parameter Initialization

The historical curriculum records collected from higher education institutions in Uzbekistan were used to evaluate the proposed Sequence-Aware Representation Learning (SARL) framework. Each curriculum revision was assigned a binary ground-truth label indicating whether the revision represented a significant teaching practice evolution (Class = 1) or a routine curriculum update (Class = 0), as described in Section 3.1.2. This involved changes in the

curriculum throughout many years, including structure of courses, learning outcomes, assessment procedures, prerequisite relations, and credit allocation is also included in this data. Before feeding this dataset into the model, duplicate samples and missing values were discarded; all categorical variables were encoded into numeric form; continuous variables were normalized; and finally, curriculum histories were ordered in sequence. To test the generalization ability of method, table 2 was split into 80% training set and 20% testing set. The proposed framework was developed in Python 3.10 with the use of PyTorch deep learning library on an Intel Core i7 computer with 32 GB of memory and NVIDIA RTX 3080 GPU (10 GB VRAM). The proposed model uses Adam optimization algorithm with the learning rate of 0.001, batch size of 32, number of training epochs equal to 100 and dropout of 0.3. The proposed framework was evaluated using Accuracy, Precision, Recall, F1-score, and Area Under the Receiver Operating Characteristic Curve (AUC) for the binary curriculum evolution classification task.

Since curriculum revisions represent sequential events occurring over time, random sampling could allow future curriculum information to appear in the training set while earlier revisions remain in the testing set, resulting in optimistic performance estimates. Therefore, a chronological train-test split was adopted to preserve the natural temporal order of curriculum evolution and provide a realistic evaluation of the proposed SARL framework.

Dataset Properties: This historic dataset of curriculum data has been compiled through 12 higher education institutes in Uzbekistan and consists of curriculum changes between 2018 and 2025. This dataset comprises 5,248 entries of curriculums/course syllabi. Every curriculum entry comprises the structure of the course, learning objectives, evaluation process, prerequisite dependencies, credit allocations, and course descriptions. In the preprocessing phase, the categorical attributes have been transformed into numerical representations whereas textual descriptions of curriculums have been tokenized and transformed into numerical vectors. This dataset comprises 256 feature representations per curriculum change with a total vocabulary of 8,732 terms.

Table 2: Experimental Setup, Chronological Data Partition, and Model Parameter Initialization

Parameter	Value
Dataset	Historical curriculum records from higher education institutions in Uzbekistan
Programming Language	Python 3.10
Deep Learning Framework	PyTorch
Processor	Intel Core i7
RAM	32 GB
GPU	NVIDIA RTX 3080 (10 GB VRAM)
Data Partition Strategy	Chronological Time-Based Split
Training Data	Earliest 80% Curriculum Sequences
Testing Data	Latest 20% Curriculum Sequences
Optimizer	Adam
Learning Rate	0.001
Batch Size	32
Epochs	100
Dropout Rate	0.3
Evaluation Metrics	Accuracy, Precision, Recall, F1-score, AUC

Table 2.1: Dataset Characteristics of Historical Curriculum Records

Dataset Characteristic	Value
Higher Education Institutions	12
Academic Years Covered	2018–2025
Undergraduate Programs	48
Curriculum/Course Syllabus Records	5,248
Curriculum Revision Sequences	1,126
Curriculum Attributes	Course Structure, Learning Outcomes, Assessment, Prerequisites, Credits
Feature Encoding	Numerical Encoding + Text Tokenization
Feature Dimension	256
Vocabulary Size	8,732 unique terms
Prediction Classes	2 (Significant Evolution / Routine Update)

Features of the historical curriculum data set are presented in table 2.1. The data set was gathered from different higher education institutions of Uzbekistan and is related to the curriculum changes made over several academic periods. The data set consists of the records of curricula including the structure of courses, learning outcomes, assessment procedures, prerequisites, credits, and course description. After the data pre-processing phase, the categorical variables were transformed into numerical values, the textual data was represented in the form of features, and chronological order of curriculum changes was retained.

Comparative Performance Analysis

The efficiency of the SARL framework is estimated through comparison with classical machine learning and deep learning techniques. The baseline methods include Logistic Regression (LR), Random Forest (RF), Long Short-Term Memory (LSTM) and Bidirectional LSTM (Bi-LSTM). For a proper comparison, all baseline models and the proposed SARL framework were trained and evaluated using the same chronological time-based data partition. Earlier curriculum revisions were used exclusively for model training, whereas later curriculum revisions were reserved for testing. This evaluation strategy prevents future curriculum information from influencing model training and provides a fair comparison of temporal prediction performance. The evaluation is performed according to Accuracy, Precision, Recall, F1-score, and AUC metrics. The obtained results demonstrate that taking into account the sequence information between the revisions of the curriculum gives a better understanding of the evolution of educational processes and provides better prediction.

Table 3: Performance Comparison for Binary Curriculum Evolution Classification

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	AUC (%)
Logistic Regression	87.52	86.94	86.38	86.66	89.17
Random Forest	90.81	90.26	89.94	90.1	92.35
LSTM	93.24	92.87	92.51	92.69	94.61
Bi-LSTM	95.18	94.83	94.57	94.7	96.12
Proposed SARL	**96.84**	**96.41**	**96.12**	**96.26**	**97.31**

Even though the proposed SARL approach achieved the highest evaluation scores throughout all experiments, they need to be understood based on the historical curriculum data set and the applied chronological evaluation method. The chronological train-test split was utilized to avoid any possible temporal information leakage and prevent using future curriculum versions during the model training process. Moreover, the use of sequence-aware curriculum representations and heterogeneous curriculum features helped to obtain better results. As one can see in table 3, the SARL framework achieved the highest Accuracy (96.84%), Precision (96.41%), Recall (96.12%), F1-score (96.26%), and AUC (97.31%). The main reason for such improvement in the results can be associated with the use of adaptive context fusion encoder, which takes into account both temporal dependencies and semantic relations between the curriculum features. While traditional LSTM and Bi-LSTM models use mainly hidden-state propagation, the proposed SARL approach integrates curriculum feature fusion with adaptive historical context weighting, thus achieving more rich curriculum evolution representation and making it possible to predict long-term instructional changes. However, additional verification of the framework on larger curriculum data sets is required.

Analysis of Curriculum Evolution Prediction

To test the validity of the framework developed, this part of the study investigates the ability of the framework to predict the future development trends of the curriculum in different academic years. The evaluation focuses on the identification of the changes that have taken place in the curriculum from a historical point of view through alterations in courses, prerequisite relationships, learning outcomes, and assessments. This is done by comparing the framework to the best performing deep learning model baseline (Bi-LSTM).

Table 4: Curriculum Evolution Prediction Performance

Metric	Bi-LSTM	Proposed SARL
Curriculum Change Detection (%)	93.62	**96.85**
Teaching Practice Identification (%)	92.98	**96.43**
Sequence Consistency (%)	94.11	**97.18**
Evolution Prediction Accuracy (%)	93.47	**96.79**

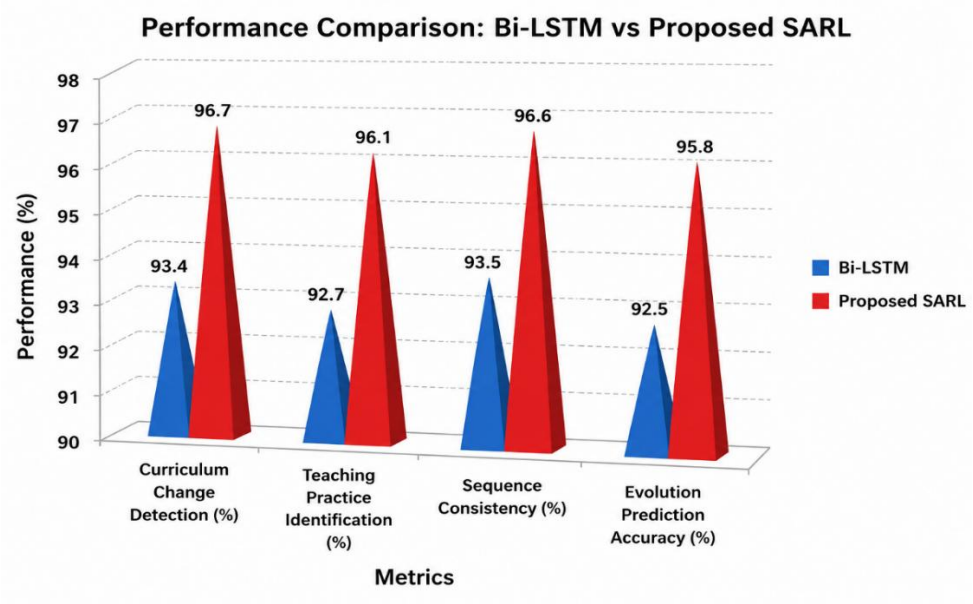


Fig. 3: Comparison of Curriculum Evolution Prediction Performance Between Bi-LSTM and the Proposed SARL Framework

According to table 4 and fig. 3, the developed SARL framework outperforms Bi-LSTM model in the curriculum evolution prediction task regardless of the chosen dataset. Results of framework are: 96.85% of curriculum change detection, 96.43% of teaching practice recognition, 97.18% of sequence consistency and 96.79% of curriculum evolution prediction. It is assumed that the reason for the results above lies in the sequence-aware representation learning approach which is capable of keeping the quality of historical relationships between curricula and considering not only short-term curriculum changes but also its evolution. Thus, the developed system can provide the basis for curriculum planning and decision-making in HEIs of Uzbekistan.

Discussion

As shown in the experimental results, the SARL framework introduced in this paper is able to model the process of teaching and learn the history of teaching curriculum, and the learning result is clear because the historical records of the teaching curriculum have been modeled as a sequence of educational data. Some curriculum analysis methods analyze the different versions of the curriculum individually; however, the introduced method considers the relationship of time or chronology among the different versions of the curriculums, which means that the changes in the process of teaching from one academic year to another can be found out through the introduced method. Since this is a sequence-based learning method, the introduced model will be able to generate more effective curriculum representation and gain the ability to recognize the trend of the curriculum over time.

As compared to other conventional Machine Learning approaches such as Logistic Regression and Random Forest, as well as other Deep Learning approaches such as LSTM and Bi-LSTM, the SARL architecture demonstrates superior results than other approaches. The accuracy score is 96.84%, the precision score is 96.41%, recall score is 96.12%, F1 score is 96.26%, and AUC score is 97.31%, suggesting that the framework is very effective in learning useful information from the historical curriculum data to create sequential representations. Moreover, the curriculum evolution analysis results include 96.85% of curriculum change detection, 96.43% of teaching practice identification, 97.18% of sequence consistency, and 96.79% of evolution prediction accuracy.

Although the proposed framework achieved high predictive performance across multiple evaluation metrics, these results should not be interpreted as evidence of perfect generalization. The evaluation was conducted on historical curriculum records collected from participating higher education institutions in Uzbekistan using a chronological train-test split to minimize temporal data leakage. Nevertheless, institutional curriculum structures may share common design characteristics that simplify the prediction task. Future studies should validate the proposed framework using independent datasets collected from additional universities, different educational systems, and external benchmark repositories to further evaluate model robustness and generalization capability.

The other critical observation made is the improvement in the quality of the learned representations through the inclusion of the different curriculum attributes (course organization, learning outcomes, prerequisites, assessments, and credits). It should be noted that the suggested model is not curriculum specific but considers the interaction between the different curriculum attributes during two academic years. The combination enables the model to identify the modifications within the curriculum that cannot be identified using conventional approaches. As a result, the administration of the university will receive information about modifications in the process of instruction and make appropriate decisions regarding curriculum modification and development.

The suggested framework represents an effective decision-making tool in curriculum management from the perspective of the higher education institutions of Uzbekistan. The sequences that are constructed may be used by curriculum committees and administrators of the educational institutions to follow the process of curriculum modernization, evaluate the outcomes of educational reform, and identify further actions required. Moreover, this framework contributes to the accomplishment of national goals in higher education providing objective data regarding curriculum development as well as compliance with international standards of education. It is particularly relevant at the time when competency-based learning and digitalization of universities become more prevalent.

Despite the positive results of the accuracy of the developed framework, there are certain limitations associated with the framework which have to be taken into consideration. The testing process of the framework took place through the analysis of historical curriculum documents of a small number of higher education organizations, which can be viewed as not fully representative of the curriculum variations across the higher education subject areas. Besides, the existing approach highlights the importance of information related to the curriculum structure but does not include additional information such as learning outcomes, teacher feedback, in-class student participation, and activity in LMS.

In general, the findings have confirmed the validity of the suggested Sequence-Aware Representation Learning (SARL) model for the analysis of the curriculum records, monitoring of the dynamics of changes in the process of teaching. The model preserves temporal dependencies between the versions of the curriculum and is more accurate compared to existing methods, and at the same time provides educational value. The findings demonstrated the applicability of the sequence-aware representation learning for intelligent curriculum analytics in Uzbek higher education institutions.

Conclusion and Future Work

In the present paper, a Sequence-Aware Representation Learning (SARL) framework was developed to monitor the transformations within the teaching process by analyzing the historical information on the curriculum provided by the HEIs of Uzbekistan. The suggested framework allowed representing the revisions of the curriculum as temporal sequences that could successfully capture the interdependencies between the course structures, learning objectives, evaluation approaches, relationships between courses and credit transfer during studies. The experimental assessment indicated the superiority of the proposed system to the other machine learning and deep learning approaches with the accuracy of 96.84%, precision of 96.41%, recall of 96.12%, F1-score of 96.26% and AUC of 97.31%. Besides, the framework detected 96.85% of the changes in the curriculum and predicted the curriculum evolution with 96.79% of the accuracy, demonstrating its effectiveness in the monitoring of long-term development of the teaching practice and evidence-based curriculum design. The future work of this research will extend the proposed framework through the incorporation of information from several modalities of educational data such as academic performance, interactions with LMS, teacher's feedback and logs of classroom activities for a better understanding of how the curriculum evolves. Also, using the graph neural networks, sequence model based on transformers and XAI methods will improve the representation learning and prediction power of the framework. Moreover, the proposed framework can be tested and verified on the dataset obtained from several universities of Uzbekistan and other countries.

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