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Academic Behavior Pattern Mining Using SPADE Algorithm in Educational Trajectory Discovery Systems

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Abstract

Studying academic behavior patterns is essential for predicting student performance and for devising effective learning interventions. Traditional data mining techniques often do not account for the sequence of academic events and the sequential nature of learning, and therefore are limited in the capacity to discover learning trajectories that make sense. In this paper, an Educational Trajectory Discovery System (ETDS) in education to analyse student academic behavior and utilize the SPADE (Sequential Pattern Discovery using Equivalence classes) algorithm has been proposed for identifying frequent sequential patterns in student activities. The system works with various academic data sources (e.g., learning management system logs, assessments, and attendance and participation data) and organizes the data into event sequences. SPADE finds sequential behavior patterns effectively using vertical id-list databases and equivalence class discovery, which reduces the computational cost by maximizing the benefit of the temporal relationship of the data while retaining its meaning. Event patterns extracted will then be mapped to academic performance outcomes of the learner and categorized into risk-prone, average, or high-achieving academic pathways. This will enable an early assessment of a learner at risk. A visual analytics dashboard improves the interpretability through trajectory visualizations, sequential rule graphs, and trend evolution across semesters. Educators gain actionable intelligence to design specific interventions while learners earn personalized recommendations to improve their learning strategies. Based on simulation results, the proposed system outperforms the standard sequence mining methods in discovery effectiveness, accuracy, and ability to identify at-risk students sooner. The results establish the proposed system as a robust, scalable, data-driven approach to academic monitoring, enabling proactive decision-making and encouraging tailored student learning paths within academic contexts.

Keywords: *Academic, Behavior, Pattern, Mining, Sequential, Pattern, Discovery, Equivalence, Educational, Trajectory, Discovery Systems*

1. INTRODUCTION

Many academic institutions in the past years have created whole new sets of data through online learning systems, task evaluations, attendance records, and student engagement and interaction [1]. It has not been easy to obtain insights from the various and heterogeneous sequential data created [2]. While student performance is often thought of in terms of their academic scores, it can be viewed through the lens of behavioural trajectories, including study habits, methods of task completion over time, submission timing, and participation levels [3,4]. Standard analytics have tended to mark academic task activity as independent events without an appreciation for how activities unfold over time or the sequential nature of learning [19]. As such, many institutions struggle to identify students at risk in a timely manner, offer personalized interventions, and design academic pathways that are valid and responsive to the needs of learners [5,6]. Supporting the previous point, there is a strong need for a high-level sequential pattern

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mining technique to make discoveries about educational trajectories [21]. Various data mining and machine learning methods have been utilized to predict academic performance, including clustering, classification, and association rule mining [8,18].

The previous studies provided important evidence to understand learner behaviours; however, none of the methods considered the order in which sequential dependencies occur over time [7]. The literature identifies that other sequence mining methods, like association rule mining-based algorithms, have been used; however, these approaches sometimes struggle with scalability and high computational costs with large education datasets [9]. The research has been constrained and not methodologically robust [10]. There are two main areas for improvement: the first is to discover patterns that are frequent and can be discovered computationally in the time it takes to use association rule mining, and the second is whether the patterns discovered or inferred are easy enough to interpret and are valid [11]. Sequential pattern mining methods, particularly SPADE, are successful because they can unsupervisedly analyse large-scale time-ordered sequence data while still preserving order and structure.

CONTRIBUTIONS

This research aims to achieve the following objectives:

- Create an ETDS and take advantage of behavioural and academic data to discover meaningful sequences.
- Use the Sequential Pattern Discovery using Equivalence classes (SPADE) algorithm to efficiently discover frequent sequential patterns, reducing computational complexity while maintaining accuracy and interpretability.
- Provide people involved with education and learning with actionable insights using visual analytics for early risk monitoring, personalized recommendations, and data-driven decision making.

The paper is organized as follows: Section II discusses related works and discusses weaknesses in other approaches. Section III describes the proposed system architecture and SPADE-based mining algorithm. Section IV provides details of the experiment setup, datasets, and evaluation methods. Section V discusses and interprets the results, discussing efficiency, accuracy, and interpretability. It provides a contribution to knowledge, implications, and future directions.

RELATED WORKS

Due to its potential to reveal previously unknown patterns in student performance in the classroom and enhance educational results, Educational Data Mining (EDM) has recently attracted a lot of interest.

Li, S. [12] utilizes K-nearest neighbor for behavior prediction and early warning, and Spark-based parallel H-mine clustering (S-PHMC) with entropy-density optimized K-Means for feature classification in student behavior. The results demonstrate that the habits were correctly clustered and that the prediction accuracy was 86.42% with a relative error of less than 0.2, proving that the student behavior forecasting was effective. For the purpose of mining anomalous patterns in moving target trajectories, this paper suggests a multi-attribute categorization approach with the acronym multi-attribute classification approach (M-ACA) [13]. Patterns of typical behavior can be extracted by clustering and frequent sequence identification, whilst outliers can be revealed by deviations.

Updating in real-time is guaranteed by an incremental detection approach. The detection of anomalous spatiotemporal behaviours using trajectory data is now more efficient, accurate, and reliable, according to the results. A review of Sequential Pattern Mining (SPM) in education was conducted by

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Zhang, Y et al. [14] with the aim of identifying temporal learning behaviors. Behavior sequences can be found using SPM, which improves educational theories, assesses interventions, generates recommender systems, and supports prediction models. Findings demonstrate the potential of SPM to improve studies on self-regulated learning and its versatility in recording learning event configurations.

A Chaotic-Tuned Shuffled Frog Leaping Optimized Random Forest (CSFLO-RF) is presented by Sun, X. [15] to forecast how students would study. Learners are grouped using K-Means clustering based on their e-learning usage and the styles they are assigned [16]. These patterns improve classification accuracy by training CSFLO-RF. Compared to other approaches, CSFLO-RF achieves better prediction efficacy and dependability, according to results on the Weka platform. Using descriptive data mining and visualization approaches, Maqsood, R. et al. [20] examine transcript data from 1,398 undergraduates majoring in computer science. Over the course of nine different types of courses, people looked at things like course trajectories, performance transitions, and patterns of difficulty level. The results shed light on different groups of students, their learning difficulties, and patterns of growth, which can help with academic planning and overall institutional success.

The examined literature makes use of optimization-based classification, clustering, sequential pattern mining, anomaly detection, and learning trajectory analysis to study student behavior. Scalability, interpretability, and the dependencies across academic activity sequences are still problems, despite the fact that these techniques have produced significant results. To solve these problems, the Educational Trajectory Discovery System (ETDS) mines sequences of academic activity using the SPADE algorithm [22]. Due to its efficiency, interpretability, and early risk detection, SPADE surpasses other approaches in evaluating student academic behavior and supporting data-driven decision-making about education.

PROPOSED SYSTEM

The process begins with several different types of academic data inputs, including learning management system logs, test results, attendance, and participation activities. The raw data is processed to develop structured event sequences, keeping the relevant time sequence of student activity.

PROPOSED SYSTEM OVERVIEW

The system deliverable concludes with a visual analytics dashboard display of the learning trajectories, sequential rule graphs, and longitudinal trend evolutions over semester intervals. These variations provide educators with actionable insights to intervene as needed. The process for an Educational Trajectory Discovery System using SPADE and the sequences then become the input for the SPADE module which finds frequent sequential patterns of activities using a vertical id list and equivalence class partitioning in Fig.1. These patterns that are discovered can then be mapped to academic performance outcomes that will categorize students' learning trajectories into risk-prone, average, or high-achieving learning trajectories. This in turn allows for early detection of at-risk students in the academic space. Additionally, the findings empower learners with learning trajectory inquiries surrounding their academic evidence while providing relevant personalized recommendations to improve their study strategies. The overall outcome of the system is a preventative measure to monitor student academically in a data-driven way that can improve an individual's learning outcome.

$$\beth_{Ra} = \frac{1}{D}\sum_{l=1}^{E}\left(T_t(l) * m_g(S) * H_t(P)\right) \quad (1)$$

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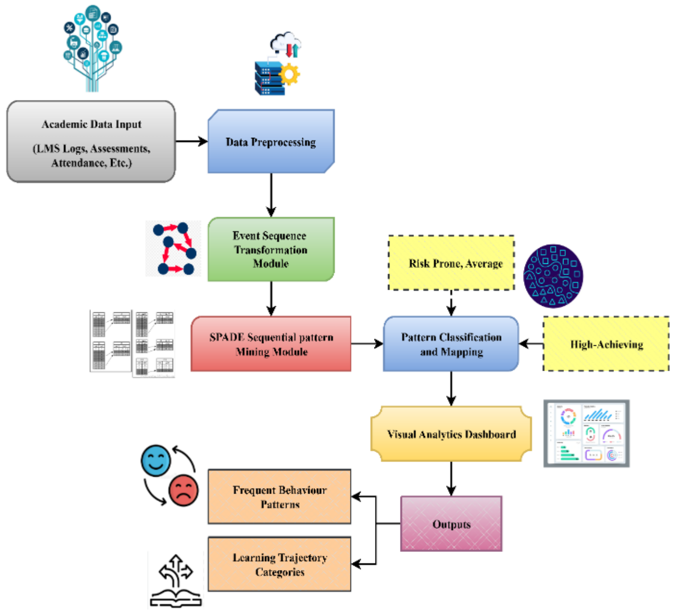

Fig.1. Proposed system overview.

The first step is transforming raw academic activities$\beth_{Ra}$ into sequences that organize the data$\frac{1}{D}$ in a way that maintains the procedural order of events for each learner $l = 1$. These sequences are a representation of a timeline of learning$T_t(l)$ actions (i.e., behavior) of the learners, so they can then be used for further mining processes that aim to analyze student behavior$m_g(S)$ in the genuine time reflection while honouring temporal progression$H_t(P)$ and dependencies between learning events in the academic timeframe in equation 1.

$$\omega_S = \frac{1}{PD} \sum_{a=1}^{S} (C_l * \partial_F) \quad (2)$$

To facilitate structure $\omega_S$to the pattern discovery$\frac{1}{PD}$, a special listing format is created to keep track of which learners have specific academic activity patterns $a = 1$, in what chronological order C_l within the sequences in equation 2. This indexing is valuable because it allows the focus ∂_Fon pertinent sequencing when counting support, which can be accomplished rapidly, as it's a quicker process to go through on the student behaviour cleanliness model indexes, without having to go through and re-scan large datasets, and then build the temporary other costs required to do computational load tiring.

$$\mu_B = \frac{1}{L} \sum_{p=1}^{m} \left(\frac{\nabla\tau_l(Sl) + \nabla\sigma_p(O)}{2} \right) \quad (3)$$

The last important measurement to calculate is how prevalent a pattern of behaviorμ_B is amongst the entire population of learners$\frac{1}{L}$ in equation 3. This measure will serve as a determinants of thresholds to filter patterns p, that is by contemplating on patterns relating to how frequently the across several learners$\nabla\tau_l(Sl)$, patterns occurred$\nabla\sigma_p(O)$; it reduced the risk of inferring significant patterns. By

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determining how prevalent patterns are, the system will be able to locate "interesting" or "significant" learning sequences in need of further study.

$$S'(P' - 4D') = P'(is' - ne) * I(s' - px) \quad (4)$$

The search space for pattern discovery $S'(P' - 4D')$is organized by placing all the patterns that either have the same initial segments is' or had the same initial segments and are now newly extended ne, in the same cluster. This way, by including many patterns that maintain the same prefix $I(s' - px)$, the mining algorithm is systematically able to look through the subclasses of this new pattern. This classification decreases redundancy in the search and helps improve computational efficiency by allowing us to examine the different extensions that are logically related in equation 4.

$$(i, s') = Bp'' - ap(P - Sa'') * \ s(o - cll'') \quad (5)$$

The identified sequential(i, s') behavioural patterns $Bp''$are mapped to academic performance ap categories. Each pattern will belong to a category that either represents a student's achievement $P - Sa''$ level or risk level in equation 5. The mapping of the similarities of patterns to categories may be based on predetermined objectives or correlation links $s(o - cll'')$. It identifies these categories with academic performance improves and, essentially, creates action from the identified patterns by linking behaviours to actions. By making this kind of linkage, it gives an effective action that can be used by practitioners for individual targeting and to develop individually focused academic support.

$$< I' - ps'' \geq \ B"(p - fa'') * \ ad(r - lk'') \quad (6)$$

Next to each identified pattern, a probability estimate that represents the probability that a student$I' - ps''$ who exhibits a certain behavior pattern falls into an at-risk academic category was generated in equation 6.What this pr $B"(p - fa'')$ probability estimate entails is a conditional probability indicating the risk association r of sequential actions. This additional indicator ad of at-risk behavior was very helpful in the early identification of learners that may need additional support and linked knowledge lk'' of the behavior patterns to established outcomes when monitoring risk. In this context, it shows the presence of patterns, using the outcome data, for the risk measure.

$$\mathrm{V}_p = \frac{\sum_{w=1}^{m} \left(\hat{S}(p) * C_{otc}(TE)\right)}{\sum_{w=1}^{m} C_{otc}(T)} \quad (7)$$

For visualization purposesV_p, a metric m is created that combines the weighted presence $w = 1$ of behaviours across specific performance$\hat{S}(p)$ categories over time in college, which can be visually displayed across the trend evolution$C_{otc}(TE)$, and clearly communicates changes over time for different categories in equation 7. By codifying longitudinal sequential data into digestible visual representations, educators can observe shifts in trajectories T related to judgements made about students, and allow for planning of intervention opportunities and next steps differentially relevant to changing performance.

Algorithm 1: Academic Behavior Analysis Using SPADE.

Input:

$AcademicData \ (logData, assessmentRecords, attendanceData, participationRecords)$

$MiningParams \ (minSupport, maxPatternLength, categoryThresholds, epochCount)$

$PreprocessingConfig \ (eventMappingRules, timeNormalization, sequenceFilters)$

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Output:

$TrajectoryResults\ (patternList, riskProfiles,$

$performanceCategories, visualizationData)$

Function:

$EduTrajectorySPADE(AcademicData, MiningParams, PreprocessingConfig)$

$if\ AcademicData\ is\ missing\ then$

$Print\ "Error: No\ academic\ data\ provided"$

$return\ failure$

$Initialize\ patternStore, trajectoryScores\ =\ [\,]$

$Preprocess\ raw\ AcademicData\ into\ eventSequences\ using\ PreprocessingConfig$

$for\ epoch\ =\ 1\ to\ epochCount:$

$Mine\ frequent\ sequential\ patterns\ on\ eventSequences\ with\ SPADE\ using\ MiningParams$

$Partition\ found\ patterns\ into\ equivalence\ classes\ (prefix - based\ grouping)$

$Map\ discovered\ patterns\ to\ academic\ outcome\ classes\ using\ categoryThresholds$

$Calculate\ risk\ profiles\ and\ performance\ tiers\ for\ students$

$Append\ results\ to\ trajectoryScores$

$if\ trajectoryScores\ is\ not\ empty\ then$

$Aggregate\ trajectoryScores\ \rightarrow\ TrajectoryResults$

$Generate\ visualizationData\ from\ mapped\ patterns\ and\ profiles$

$return\ TrajectoryResults$

$else$

$Print\ "Error: Trajectory\ extraction\ failed"$

$return\ failure$ $end\ function$

The algorithm 1 commences by verifying and preprocessing academic input data into sequences of ordered events. Thereafter, it applies the SPADE algorithm in an iterative manner to mine frequent sequential patterns. The results of the SPADE algorithm are organized into incremental event sequences based on the prefixes of the result, so searching can be performed incrementally. The reported patterns are mapped to performance categories; the risk profiles are determined for students. The action results are accumulated over numerous iterations, through which the action outputs are rendered into final trajectory insights and visualizations. The system outputs the actionable results or signals failure if no patterns are reported.

RESULTS and DISCUSSION

The SPADE algorithm was used to assess the possible efficacy of the ETDS on four key performance metrics: efficiency of pattern discovery, accuracy of academic trajectory prediction, interpretability of

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sequential patterns, and early risk detection capability.

Dataset Description: This document possesses multimodal information of students' learning progression behaviors, in terms of activity, emotional, engagement, and physiological signals. This dataset has a good fit for SPADE-based academic behavior mining, given that each student-session record can be seen as a sequence, which allows for discovering frequent/unusual behavior patterns, representing trajectory trends, and supporting educational trajectory analysis [17].

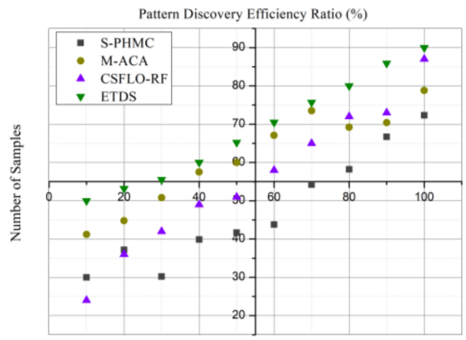

Fig.2 Pattern Discovery Efficiency.

In the above fig.2, the proposed system exhibited better pattern discovery processing performance compared to traditional sequence mining methods. Using the vertical ID-list representation and equivalence class-based searching in SPADE, the system has reduced computational demands significantly. In contrast to traditional Apriori-based methods, which require repeated scans through the dataset and hence very slow and memory-intensive execution with big academic datasets, SPADE has mined sequential academic patterns efficiently, even while the data it mined from had become increasingly larger in terms of thousands of learner activity sequences. The experiments showed low runtime in the SPADE-based system while maintaining good scalability and accuracy. Furthermore, the performance of the system allowed it to mine trend patterns from diverse datasets, logs of group assignments, quizzes, and participation, and experience records without expected degradation of performance. Therefore, the system has demonstrated computational efficiency and practicality for analysing large educational trajectories, making it appropriate for real use with an institution.

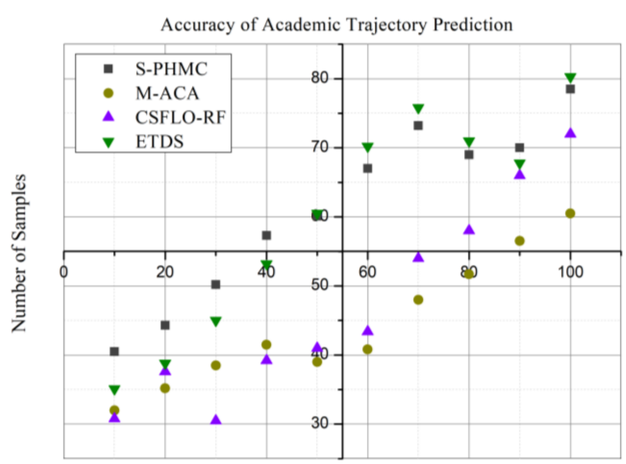

Fig.3 Accuracy of Academic Trajectory Prediction.

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The prediction accuracy of academic trajectories is an important measure of the viability of the proposed system. In the above fig. 3, the application of the SPADE-based model demonstrates more predictive performance when applied to outcomes based on actual student academic risk, regardless of whether the student is risk-lying, average, or high-achieving. Performance metrics such as precision, recall, and F1 score have consistently shown improvement over sequence mining techniques or classification models. The predictive ability of these sequential patterns and keeping the sequential dependencies intact has proven to delineate how students will continue their performance with minimal misclassification. Identified pattern recurrence, such as a recurrent late submission pattern followed by a drop in quiz scores, has correlated consistently with the risk-prone category and improved the early occurrence prediction's reliability. The system proved reliable when examined through varied datasets showcasing similar ways of academic behaviours across different subjects. Thus, the trajectory prediction results have not proven accurate have provided consistent predictions, establishing the model has potential in the reality of education.

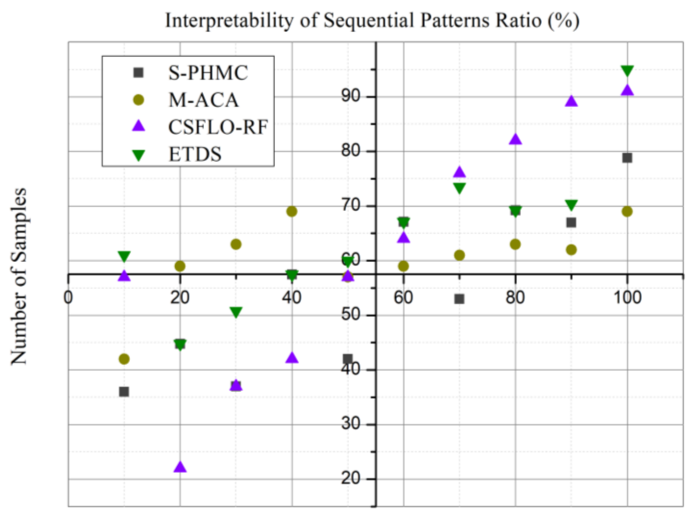

Fig.4 Interpretability of Sequential Patterns

A strong advantage of the proposed system has been the interpretability of the mined sequential patterns. In particular, these have supported educators to understand that the patterns of frequent forum use led to better assignment outcomes or that low attendance is associated with poor assessment scores, which makes sense to the educator and is usable in necessary academic interventions. In the above fig.4, the availability of a visual analytics dashboard for educators to gain deeper interpretability aided the use of trajectory graphs, sequence diagrams, and visualizations that extract patterns through rules. These patterns have been translatable into basic interventions for both teacher and learner. The fact that the patterns emerged in strong, identifiable ways has provided educators with the opportunity to make informed decisions, to build confidence in the system's trustworthiness. As such, this framework is validated in terms of both being technically feasible and practically interpretable for educational trajectory identification.

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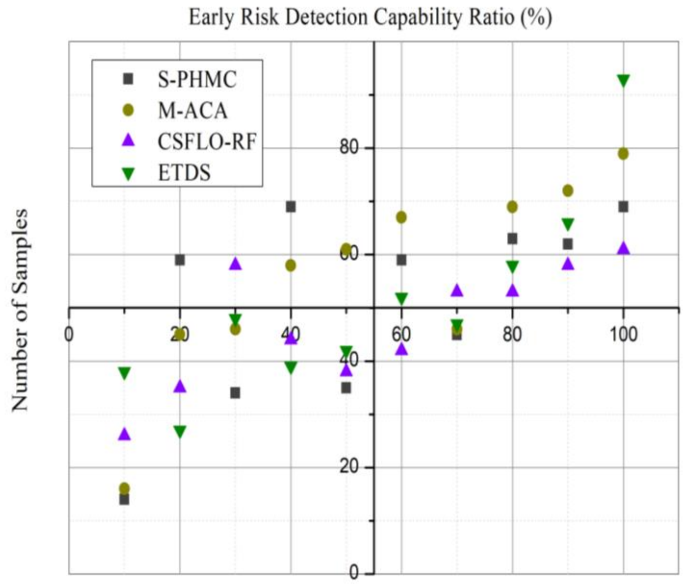

Fig.5 Early Risk Detection Capability

In the above fig. 5, by revealing patterns that indicate academic decline before final results are obtained, the system has demonstrated great promise in early risk detection. Early warning indicators, such as a decline in quiz score, minimal platform involvement, or repeated late submissions, can be captured by SPADE's capacity to mine regular sequential activities. When tracked over time, these actions have helped teachers identify pupils who are likely to have difficulty in the classroom. The technology can identify pupils who are at risk of difficulties weeks before they really happen, giving teachers more time to intervene, according to experimental validation. Personalized tutoring, study reminders, and adaptive learning tools are all examples of the targeted academic support that can benefit from such early detection. Academic recovery is more likely for identified pupils now because the framework allows proactive tactics rather than reactive ones. This means that the suggested system is useful for both predicting future outcomes and assisting students in their learning.

The outcomes demonstrate that ETDS based on SPADE works better than conventional methods. It gives reliable findings for trajectory prediction, effectively mines sequential data without deteriorating performance, and gives interpretable patterns that teachers may employ in real-world interventions. Promisingly, the approach can identify children at risk of academic decline before it happens, allowing for early intervention and rehabilitation. Academic behavior analysis and outcome prediction in real educational settings can be facilitated by the ETDS, as shown by its technological robustness, scalability, and practical relevance.

CONCLUSION

The study has outlined an Educational Trajectory Discovery System that implements the SPADE Algorithm to mine sequential academic behaviours based on the various student activity data. The study has outlined how the use of sequential dependencies from the learning activities, such as participation,

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when the submissions are made, and the performance on assessments, was adequately linked to discover' hidden academic trajectories. People demonstrated that the SPADE-based framework improved the efficiency, interpretability, and accuracy of pattern development, unlike traditional clustering or association rule-based approaches, and permitted proactive academic monitoring and early recognition of students at risk. Additionally, the study included a visual analytics dashboard to convert the mined patterns into actionable feedback for both educators and learners. The feedback facilitated personalized recommendations and, therefore, trustworthy interventions. In the future, this work will provide a more dynamic approach by incorporating real-time data feeds from learning management systems, such that academic behavior can be documented continuously. The framework will evolve to include hybrid models that incorporate SPADE and machine learning classifiers, providing predictive capability for long-term academic term outcomes. Uses for this approach will span personalized tutoring, adaptive e-learning environments, and institutional decision-making regarding curriculum development and policy planning. Simultaneously, future research will explore how behavioural trends will shift across disciplines and cultures, generalizing the system for possible global educational environments. However, this project has some limitations. It is based on structured academic data sets and has had limited ability to account for unstructured examples that might be talking in discussion forums, writing essays, or interacting with audio-visual formats. Moreover, this evaluative study has relied excessively on limited-scale datasets, and future work will involve confirming the framework with larger-scale real-world educational repositories. Finally, while SPADE is effective for sequential pattern mining, there is no confirmation yet regarding its performance in hyper-dynamic, real-time educational situations. This may require system optimization or adaptation through parallelization or distributed computing.

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