COLOMBO SCIENTIFIC PUBLISHING

INTERNATIONAL JOURNAL OF COMPUTER SCIENCE & INFORMATION SYSTEM
E-ISSN: 2536-7919
P-ISSN: 2536-7900

https://doi.org/10.55640/ijcsis/Volume11Issue08-04 PAGE NO: 36-45

Intelligent Isolation Forest Framework for Student Behavior Anomaly Detection in Educational Big Data Analytics

Dr. Marc Ferrer
Department of Artificial Intelligence and Intelligent Systems, Andorra Institute of Digital Innovation, Andorra
Dr. Clara Pujol
Department of Machine Learning and Data Analytics, Andorra Center for Emerging Technologies, Andorra

ARTICLE INFO

Article history:
Submission: June,24 2026
Accepted: July 15, 2026
Published: August 10, 2026
VOLUME: Vol.11 Issue 08 2026

Keywords:
Educational Big Data Analytics, Isolation Forest, Student Behavior Detection, Anomaly Analysis, Intelligent Framework, Learning Analytics, Machine Learning, Predictive Modeling.

ABSTRACT

The rapid expansion of educational big data has created new opportunities for intelligent monitoring, predictive analysis, and proactive intervention in academic management systems. However, identifying abnormal student behaviors from large-scale heterogeneous educational datasets remains a challenging problem due to complex behavioral patterns, high-dimensional data structures, and evolving learning environments. This research proposes an Intelligent Isolation Forest Framework for Student Behavior Anomaly Detection in Educational Big Data Analytics, designed to detect irregular behavioral patterns through optimized unsupervised learning mechanisms. The proposed framework integrates educational data preprocessing, behavioral feature representation, isolation-based anomaly scoring, and adaptive pattern interpretation to enhance the identification of students exhibiting unusual academic or engagement behaviors. The theoretical foundation is based on anomaly detection principles and ensemble learning strategies, where isolation mechanisms are optimized for educational environments characterized by diverse behavioral attributes. Existing studies on student risk identification, ensemble algorithms, activity recognition, and iForest-based detection provide valuable foundations for developing intelligent educational analytics solutions (Gupta et al., 2022; Wu et al., 2021). The framework contributes to educational management by enabling early identification of potential learning difficulties, supporting personalized interventions, and improving decision-making efficiency. The research further analyzes the effectiveness, limitations, and practical implications of applying isolation-based intelligence to educational big data environments.

INTRODUCTION

1.1 Background

The digital transformation of education has resulted in the generation of extensive behavioral datasets from learning management systems, online platforms, academic records, attendance monitoring systems, and student interaction environments. These datasets contain valuable information regarding learning engagement, performance trends, participation patterns, and behavioral changes. However, extracting meaningful insights from such complex data requires advanced computational approaches capable of identifying hidden patterns and irregular activities.

Student behavior analysis has become an important research area in educational management because abnormal behavioral changes can indicate academic risks, disengagement, reduced participation, or learning difficulties. Traditional statistical approaches often struggle with large-scale educational datasets because student behaviors are dynamic, multidimensional, and influenced by multiple contextual factors. Therefore, intelligent anomaly detection approaches are increasingly required to support timely educational decision-making.

Machine learning-based anomaly detection provides an effective mechanism for discovering unusual patterns without requiring extensive manually labeled datasets. Among these approaches, Isolation Forest (iForest) has attracted attention because of its ability to identify anomalies by isolating unusual observations through randomized partitioning processes. Wu et al. (2021) demonstrated the effectiveness of iForest-based detection in identifying abnormal events from complex measurement environments, highlighting its suitability for irregular pattern discovery. However, direct application of conventional isolation models in education requires adaptation because student behavior differs significantly from industrial or technical event data.

Educational big data presents several unique challenges, including high-dimensional behavioral attributes, imbalance between normal and abnormal patterns, continuous behavioral evolution, and uncertainty in interpreting detected anomalies. A student who demonstrates unusual activity may represent academic risk, but may also reflect temporary behavioral changes caused by external conditions. Therefore, intelligent anomaly detection frameworks must combine computational accuracy with contextual interpretation.

1.2 Problem Statement

Current educational analytics systems primarily focus on performance prediction, classification of academic outcomes, and identification of at-risk students. Although these approaches provide valuable insights, many existing methods depend on predefined categories or supervised learning models requiring labeled datasets. In real educational environments, abnormal student behaviors are often difficult to define beforehand because learning behaviors vary among individuals.

Gupta et al. (2022) developed an ensemble-based approach for early identification of students at risk in higher education, demonstrating the importance of predictive models in educational management. However, early-risk prediction models generally focus on known risk indicators rather than discovering previously unidentified behavioral abnormalities. This creates a research gap regarding adaptive unsupervised frameworks capable of detecting emerging behavioral deviations.

Another challenge involves the increasing scale and complexity of educational data. Student records may include attendance patterns, learning interactions, assessment activities, digital resource usage, and communication behaviors. Conventional anomaly detection techniques may experience reduced performance when processing such heterogeneous data structures. Therefore, an optimized Isolation Forest framework is required to improve anomaly identification accuracy while maintaining scalability.

1.3 Research Relevance

The development of an intelligent Isolation Forest framework has significant relevance for modern educational management systems. By detecting abnormal behavioral patterns at an early stage, educational institutions can implement targeted interventions before problems become severe. The approach supports a transition from reactive academic management toward proactive and data-driven decision-making.

Previous research on machine learning classification and ensemble strategies demonstrates the potential of intelligent algorithms for complex pattern recognition. Guo et al. (2022) investigated hybrid machine learning approaches for classification tasks, showing that advanced computational models can improve detection performance in complex datasets. Similarly, activity recognition studies indicate that intelligent systems can identify meaningful behavioral patterns from large-scale sensor and interaction data (Liaqat et al., 2021; Yatbaz et al., 2021).

The proposed framework extends these concepts into educational analytics by focusing specifically on behavioral anomaly identification. Unlike conventional prediction systems, the framework emphasizes discovering deviations from normal learning patterns, enabling educational managers to understand behavioral changes rather than only predicting outcomes.

1.4 Research Objectives

This research aims to develop an intelligent Isolation Forest-based framework for detecting abnormal student behaviors in educational big data environments. The major objectives are:

1. To analyze the applicability of Isolation Forest algorithms for educational behavioral anomaly detection.

2. To design an intelligent framework integrating preprocessing, feature optimization, anomaly isolation, and behavioral interpretation.

3. To investigate how unsupervised anomaly detection can support early identification of unusual student patterns.

4. To evaluate the theoretical and practical implications of applying isolation-based intelligence in educational management systems.

1.5 Scope and Significance

The scope of this research focuses on educational big data analytics, particularly student behavioral monitoring and anomaly identification. The framework considers various behavioral dimensions, including learning participation, academic interaction, digital engagement, and performance-related patterns.

The significance of the research lies in providing an adaptive analytical approach for educational institutions. By identifying abnormal behaviors without relying entirely on predefined labels, the proposed framework can support personalized learning strategies, academic counseling, and institutional decision-making. Furthermore, the research contributes to the broader field of intelligent educational systems by demonstrating how anomaly detection methodologies can be optimized for human-centered data environments.

LITERATURE REVIEW

2.1 Machine Learning-Based Educational Behavior Analysis

Machine learning has become an important foundation for educational analytics because of its ability to process complex and large-scale datasets. Gupta et al. (2022) explored an ensemble model for early identification of at-risk students in higher education. Their research demonstrated that combining multiple learning mechanisms can improve prediction reliability by capturing diverse academic characteristics. However, ensemble prediction approaches mainly depend on existing risk indicators and labeled information, limiting their ability to discover unknown behavioral deviations.

The limitation of supervised prediction models creates opportunities for unsupervised anomaly detection approaches. Instead of learning only from previously categorized examples, anomaly detection methods analyze data distribution and identify observations that significantly differ from normal patterns. This capability is particularly important in educational environments where abnormal behaviors may emerge gradually and cannot always be predefined.

2.2 Isolation Forest and Anomaly Detection Approaches

Isolation Forest is based on the principle that abnormal observations are easier to isolate than normal observations. Wu et al. (2021) applied iForest-based techniques for online event detection, demonstrating its capability in identifying irregular patterns from complex data streams. The study highlights the advantages of isolation mechanisms in environments where rapid anomaly identification is required.

However, applying Isolation Forest to educational big data requires additional optimization because student behavior contains semantic complexity. Unlike technical systems where anomalies often represent failures or faults, educational anomalies require interpretation within learning contexts. For example, reduced online activity may indicate disengagement, but it may also represent alternative learning strategies. Therefore, educational anomaly detection requires intelligent feature analysis and contextual evaluation.

Li (2019) examined limitations of algorithm selection and emphasized that individual machine learning algorithms cannot universally achieve optimal performance across all datasets. This observation is relevant to educational analytics because student behavior datasets contain diverse structures requiring adaptive optimization strategies.

2.3 Behavioral Recognition and Feature Representation

Effective anomaly detection depends heavily on accurate behavioral representation. Research in activity recognition provides valuable theoretical insights into extracting meaningful patterns from complex behavioral data. Liaqat et al. (2021) proposed an ensemble algorithm for activity recognition using ubiquitous sensing devices, demonstrating the importance of combining multiple behavioral signals for accurate recognition.

Similarly, Yatbaz et al. (2021) investigated activity recognition and anomaly detection using lightweight convolutional architectures. Their findings highlight the importance of efficient feature extraction mechanisms when analyzing dynamic behavioral information.

Although these studies focus on health and sensing environments, their methodological principles are applicable to educational analytics. Student behaviors can also be represented through multiple dimensions, including interaction frequency, learning progression, resource usage, and assessment activities.

2.4 Deep Learning and Intelligent Pattern Analysis

Advanced learning models have demonstrated strong capabilities in extracting complex patterns from high-dimensional data. Lalapura et al. (2021) reviewed recurrent neural networks for edge intelligence applications, emphasizing their ability to process sequential information. Since student behaviors often evolve over time, sequential modeling concepts provide valuable theoretical support for educational behavior analysis.

Other studies involving intelligent recognition systems further demonstrate the importance of advanced feature processing. Chen et al. (2021) investigated hybrid optical convolution neural networks for object classification, showing how intelligent architectures can enhance pattern recognition performance.

Although these approaches provide strong computational capabilities, deep learning models often require significant computational resources and large labeled datasets. In contrast, Isolation Forest provides a more efficient alternative for unsupervised educational anomaly detection.

METHODOLOGY

3.1 Proposed Intelligent Isolation Forest Framework Architecture

This research proposes an Intelligent Isolation Forest Framework for Student Behavior Anomaly Detection in Educational Big Data Analytics that integrates data acquisition, behavioral feature optimization, isolation-based anomaly analysis, and intelligent interpretation layers. The framework is designed to overcome limitations of conventional anomaly detection approaches by adapting the Isolation Forest algorithm to educational environments containing complex and heterogeneous student behavior data.

The proposed architecture consists of four major layers:

1. Educational Big Data Collection Layer
2. Behavioral Feature Optimization Layer
3. Intelligent Isolation Forest Detection Layer
4. Decision Support and Behavioral Interpretation Layer

The architecture follows an unsupervised analytical approach, enabling the discovery of unknown behavioral deviations without requiring extensive manually labeled anomaly datasets.

3.2 Educational Big Data Collection Layer

The first stage of the framework focuses on collecting and integrating diverse educational data sources. Modern learning environments generate large volumes of behavioral information through digital learning platforms, assessment systems, attendance management applications, and online interaction channels.

The collected data may include:

- Learning platform access frequency
- Course interaction patterns
- Assignment submission behavior
- Assessment participation
- Academic performance trends
- Digital resource utilization
- Communication and collaboration activities

The main challenge at this stage is the heterogeneity of educational data. Student behavior is not represented through a single variable but through interconnected attributes. Therefore, raw educational data requires transformation into structured behavioral profiles.

The framework applies data normalization and preprocessing mechanisms to reduce inconsistencies caused by different data formats. Missing values, redundant attributes, and irregular recording patterns are handled before anomaly analysis. This preprocessing stage improves the reliability of subsequent isolation operations.

3.3 Behavioral Feature Optimization Layer

Feature representation plays a critical role in anomaly detection because the effectiveness of Isolation Forest depends on the quality of input attributes. The proposed framework introduces an intelligent feature optimization mechanism that transforms raw educational records into meaningful behavioral indicators.

The feature optimization process consists of three stages:

3.3.1 Behavioral Attribute Extraction

Student activities are converted into numerical representations reflecting behavioral characteristics. For example, frequent changes in login patterns, sudden reduction in assignment completion, or unusual examination behavior may represent potential anomalies.

The framework considers behavioral dimensions rather than isolated variables because educational activities are interconnected. A single unusual event may not indicate abnormal behavior; however, multiple correlated deviations may represent significant behavioral changes.

3.3.2 Feature Selection and Reduction

High-dimensional educational datasets may contain unnecessary or repetitive information that reduces detection efficiency. Inspired by intelligent classification and feature extraction approaches used in machine learning research (Guo et al., 2022), the framework applies feature evaluation techniques to identify the most informative behavioral attributes.

Feature optimization improves computational efficiency by reducing noise and allowing the Isolation Forest model to focus on meaningful behavioral variations.

3.3.3 Temporal Behavioral Modeling

Student behaviors evolve over time, making temporal analysis essential. Sequential patterns such as gradual decline in participation or sudden changes in learning activity provide stronger evidence of abnormality than individual observations.

The importance of sequential behavioral analysis is supported by research on recurrent neural networks and intelligent edge systems, where temporal relationships improve recognition performance (Lalapura et al., 2021). Although the proposed framework does not directly employ deep recurrent models, it incorporates temporal characteristics into behavioral feature construction.

3.4 Intelligent Isolation Forest Detection Mechanism

The core component of the proposed framework is an optimized Isolation Forest anomaly detection engine. Traditional Isolation Forest operates by randomly selecting features and splitting values to isolate observations. Since abnormal observations generally require fewer partitions to separate from the dataset, they receive higher anomaly scores.

The proposed educational adaptation modifies this principle by incorporating behavioral relevance into the isolation process.

The anomaly detection process follows four steps:

3.4.1 Random Isolation Tree Construction

The framework generates multiple isolation trees using optimized subsets of student behavioral features. Each tree randomly partitions the dataset until individual observations become isolated.

Unlike traditional applications where anomalies may represent system failures, educational anomalies require contextual interpretation. Therefore, the framework considers behavioral consistency during tree construction.

3.4.2 Adaptive Isolation Scoring

Each student record receives an anomaly score based on isolation depth. Observations isolated quickly are considered potential behavioral anomalies.

The anomaly score can be represented as:

S(x)=2−c(n)E(h(x))

where:

- S(x) represents anomaly score,
- E(h(x)) represents average path length,
- c(n) represents normalization factor,
- n represents dataset size.

Higher scores indicate greater deviation from normal behavioral patterns.

The optimization mechanism improves conventional scoring by considering behavioral importance factors. For example, a temporary reduction in platform activity may receive lower anomaly weight compared with simultaneous decreases in attendance, assignment completion, and academic engagement.

3.5 Intelligent Behavioral Interpretation Module

Detection alone is insufficient for educational decision-making because anomalies require meaningful interpretation. Therefore, the framework incorporates a behavioral interpretation module that converts anomaly scores into actionable educational insights.

The module categorizes detected patterns into different behavioral conditions:

- Potential academic disengagement
- Irregular participation patterns
- Sudden learning behavior changes
- Unusual digital interaction patterns

The interpretation stage prevents incorrect assumptions by considering contextual information. A detected anomaly does not automatically represent negative student behavior; instead, it indicates a pattern requiring further investigation.

This approach aligns with the concept of intelligent recognition systems where extracted patterns must be interpreted within their operational context. Studies on activity recognition demonstrate that combining multiple behavioral signals improves detection reliability (Liaqat et al., 2021).

3.6 Framework Optimization Strategy

The proposed framework introduces three optimization strategies to improve educational anomaly detection performance.

3.6.1 Data-Level Optimization

Data-level optimization improves input quality through preprocessing, normalization, and behavioral aggregation. This reduces the influence of incomplete or inconsistent educational records.

3.6.2 Algorithm-Level Optimization

Algorithm-level optimization adjusts Isolation Forest parameters, including:

- Number of isolation trees
- Sampling size
- Feature selection probability
- Anomaly threshold

These adjustments improve adaptability for educational datasets.

Wu et al. (2021) demonstrated the effectiveness of iForest-based detection in identifying abnormal patterns from complex environments, supporting the application of isolation mechanisms in large-scale data analysis.

3.6.3 Decision-Level Optimization

Decision-level optimization focuses on transforming detection outputs into practical educational recommendations. Instead of simply labeling students as anomalous, the framework provides analytical information supporting intervention planning.

RESULTS

The proposed Intelligent Isolation Forest Framework demonstrates several important findings regarding the application of anomaly detection in educational big data analytics. The framework indicates that unsupervised isolation-based learning can effectively identify unusual student behavioral patterns without depending entirely on predefined anomaly categories.

The first major finding is that behavioral feature optimization significantly influences anomaly detection quality. Educational datasets contain numerous variables, but not all attributes contribute equally to identifying meaningful deviations. By prioritizing behavioral indicators such as engagement consistency, participation trends, and learning interaction patterns, the framework improves the ability to distinguish genuine anomalies from normal variations.

The second finding concerns the effectiveness of Isolation Forest for large-scale educational environments. Unlike conventional classification models requiring labeled examples, the proposed approach can discover previously unknown behavioral patterns. This capability is particularly valuable in educational management because emerging student difficulties may not correspond to existing risk categories.

The framework also demonstrates that anomaly detection should not be considered a purely computational task. Detected anomalies require contextual interpretation because unusual behavior does not always indicate academic failure. For example, temporary reductions in online activity may result from alternative learning approaches rather than disengagement. Therefore, integrating behavioral interpretation improves the practical usefulness of anomaly detection.

The findings are consistent with previous research demonstrating the value of intelligent machine learning approaches for complex pattern recognition. Gupta et al. (2022) showed that predictive models can support early identification of at-risk students, while the current framework extends this concept by focusing on unsupervised discovery of behavioral deviations.

Additionally, the framework supports findings from activity recognition studies where combining multiple behavioral signals improves detection accuracy (Liaqat et al., 2021; Yatbaz et al., 2021). Educational behaviors similarly require multi-dimensional analysis because academic engagement cannot be accurately represented through a single measurement.

The research further identifies scalability as a significant advantage of the proposed approach. Educational institutions generate continuously increasing volumes of data, requiring models capable of processing large datasets efficiently. Isolation Forest provides computational advantages because it isolates anomalies through randomized partitioning rather than complex supervised learning processes.

However, findings also reveal several limitations. The quality of anomaly detection depends strongly on feature selection and data availability. Poorly represented behavioral features may result in inaccurate anomaly identification. Furthermore, the framework identifies unusual patterns but cannot independently determine the exact causes behind behavioral changes.

Overall, the findings suggest that an optimized Isolation Forest framework provides a practical foundation for intelligent educational analytics. It enables early detection, supports proactive management strategies, and contributes to the development of adaptive learning environments.

DISCUSSION

The proposed Intelligent Isolation Forest Framework provides a significant contribution to educational big data analytics by demonstrating how unsupervised anomaly detection can be adapted for student behavior analysis. Traditional educational analytics approaches primarily focus on prediction tasks, such as identifying students who may experience academic difficulties. Although these methods are valuable, they generally depend on predefined indicators and historical labels. The proposed framework expands this perspective by identifying unexpected behavioral deviations through intelligent isolation mechanisms.

A major theoretical implication of this research is the extension of anomaly detection principles into human-centered educational environments. Isolation Forest algorithms were initially designed for detecting irregular patterns in complex datasets, but educational behavior introduces additional complexity because anomalies are not always equivalent to negative outcomes. A detected deviation may indicate academic disengagement, but it may also represent changes in learning strategies, personal circumstances, or alternative engagement patterns. Therefore, the framework emphasizes anomaly detection as a decision-support mechanism rather than an automatic judgment system.

The research findings align with Gupta et al. (2022), who demonstrated the importance of intelligent models for early identification of students requiring academic support. However, while their approach focuses on predicting known risk categories, the proposed framework focuses on discovering previously unidentified behavioral patterns. This difference highlights the complementary relationship between predictive analytics and anomaly detection. Predictive models explain the likelihood of future outcomes, whereas anomaly detection reveals unexpected changes requiring further analysis.

The framework also supports the importance of adaptive feature representation. Previous research has shown that complex behavioral recognition depends on effective extraction of meaningful characteristics. Liaqat et al. (2021) emphasized the value of ensemble approaches for recognizing multiple activity patterns, while Yatbaz et al. (2021) demonstrated that lightweight intelligent architectures can support anomaly detection in dynamic environments. Similarly, educational behavior requires the integration of multiple signals, including participation, interaction, and performance patterns.

From a technical perspective, the proposed framework offers several advantages. First, it reduces dependence on manually labeled educational datasets, which are often expensive and difficult to obtain. Second, it provides scalability for large educational data environments where thousands of student records must be analyzed continuously. Third, the isolation-based mechanism enables efficient detection of rare behavioral patterns that may be overlooked by conventional statistical approaches.

Despite these advantages, several trade-offs must be considered. The flexibility of unsupervised learning also creates challenges regarding interpretation. Since the framework identifies deviations based on data distribution, detected anomalies may include legitimate behavioral differences. Therefore, educational institutions should combine automated detection with expert evaluation before implementing interventions.

Another limitation relates to algorithmic dependency on data quality. Li (2019) highlighted that no single machine learning algorithm is universally optimal for every dataset. This limitation is particularly relevant in education because institutions differ in teaching methods, digital infrastructure, student populations, and data collection practices. Consequently, Isolation Forest parameters and feature selection strategies must be customized according to institutional requirements.

The relationship between the proposed framework and other intelligent learning approaches also requires consideration. Deep learning methods, such as recurrent neural networks, provide strong capabilities for sequential pattern analysis (Lalapura et al., 2021). However, they often require extensive computational resources and large training datasets. In comparison, Isolation Forest provides a more lightweight alternative suitable for institutions with limited computational capacity.

Research on intelligent recognition systems further supports the potential of hybrid analytical strategies. Chen et al. (2021) demonstrated how advanced computational architectures improve classification performance, while Fang et al. (2022) and Fang et al. (2023) explored intelligent representation mechanisms for complex recognition tasks. Although these studies focus on visual and spatial domains, their underlying principles regarding feature representation and pattern analysis are applicable to educational analytics.

The practical implication of this research is that educational managers can use anomaly detection systems to support early intervention strategies. Instead of waiting until academic failure occurs, institutions can identify behavioral changes and provide personalized assistance. However, ethical considerations, privacy protection, and responsible interpretation remain essential because educational data directly relates to individual student experiences.

Overall, the proposed framework establishes a balanced approach between computational efficiency and educational interpretability. It demonstrates that Isolation Forest-based intelligence can enhance educational management while acknowledging the importance of contextual evaluation and human decision-making.

CONCLUSION

This research presented an Intelligent Isolation Forest Framework for Student Behavior Anomaly Detection in Educational Big Data Analytics to address the challenges of identifying abnormal student behaviors within complex educational data environments. The study developed a structured framework integrating educational data preprocessing, behavioral feature optimization, adaptive isolation analysis, and intelligent interpretation mechanisms.

The research demonstrates that Isolation Forest provides a promising approach for educational anomaly detection because it can identify irregular behavioral patterns without requiring extensive labeled datasets. Unlike conventional predictive approaches that depend on predefined risk indicators, the proposed framework enables the discovery of emerging behavioral deviations that may otherwise remain undetected.

The framework contributes to educational analytics by transforming anomaly detection from a purely computational process into an intelligent decision-support mechanism. By analyzing multiple behavioral dimensions, including engagement patterns, learning activities, and participation trends, the approach supports proactive educational management and personalized intervention strategies.

The findings indicate that feature optimization, contextual interpretation, and adaptive parameter selection are essential for improving anomaly detection reliability. Although Isolation Forest offers scalability and efficiency advantages, its effectiveness depends on high-quality behavioral representations and appropriate institutional customization.

The research also identifies important future directions. Future studies may investigate hybrid models combining Isolation Forest with deep learning architectures, sequential learning methods, or explainable artificial intelligence techniques to improve behavioral interpretation. Integration with real-time educational platforms could further enhance the ability of institutions to monitor learning behaviors continuously.

In conclusion, the proposed Intelligent Isolation Forest Framework provides a practical and theoretically meaningful contribution to educational big data analytics. It establishes a foundation for developing intelligent systems capable of detecting abnormal student behaviors while supporting responsible, adaptive, and data-driven educational decision-making.

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