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Intelligent Classification Approach for Identifying Key Determinants of Student Achievement in Higher Education

Dr. Julien Weber
Department of Artificial Intelligence and Data Engineering Luxembourg Institute of Digital Intelligence Luxembourg City, Luxembourg,

Dr. Sophie Muller
Center for Machine Learning Research European AI Innovation Laboratory Esch-sur-Alzette, Luxembourg

ABSTRACT

The increasing complexity of higher education environments has created a strong demand for data-driven approaches capable of identifying the factors influencing student achievement. Academic performance is shaped by multiple interacting elements, including learning behaviors, educational resources, technological engagement, and individual academic characteristics. This research presents an intelligent classification approach for identifying key determinants of student achievement in higher education by integrating educational data mining concepts and artificial intelligence-based classification strategies. The study synthesizes existing research on educational profiling, performance prediction, technology-supported learning, and dropout analysis to establish a conceptual framework for analyzing academic success patterns. Previous studies demonstrate that classification techniques can reveal hidden relationships between learner characteristics and educational outcomes, supporting evidence-based academic decision-making (Akazaki et al., 2020; Yılmaz & Sekeroglu, 2020). The proposed approach emphasizes feature identification, learner categorization, and predictive interpretation to support early intervention and personalized educational strategies. Findings indicate that intelligent classification models can enhance institutional understanding of student achievement determinants while addressing challenges related to data complexity, interpretability, and contextual variation. The research contributes a structured analytical perspective for higher education institutions seeking to improve academic outcomes through intelligent decision-support mechanisms.

KEYWORDS: Intelligent Classification, Educational Data Mining, Student Achievement Prediction, Artificial Intelligence, Higher Education Analytics, Learning Performance, Predictive Modeling, Academic Success Factors.

INTRODUCTION

1.1 Background

Higher education institutions increasingly generate large volumes of academic, behavioral, and technological data through learning management systems, assessment platforms, and digital educational environments. These data sources provide opportunities to understand student learning patterns and identify factors associated with academic achievement. However, traditional evaluation approaches often depend on limited academic indicators such as examination scores or cumulative grades, which may not sufficiently capture the complex relationship between learner characteristics and educational success.

Educational data mining has emerged as an important research domain for extracting meaningful patterns from educational datasets. Through analytical methods and classification techniques, institutions can examine student profiles, detect performance variations, and develop predictive models that support academic planning. Akazaki et al. (2020) demonstrated the importance of educational data mining in identifying learner profiles by analyzing characteristics of candidates within an educational context. Their study highlights how structured data analysis can reveal meaningful patterns among diverse student groups.

Artificial intelligence-based classification techniques provide advanced capabilities for transforming educational data into actionable knowledge. Classification models can categorize students according to achievement levels, identify risk patterns, and determine influential variables associated with academic outcomes. Yılmaz and Sekeroglu (2020) emphasized that artificial intelligence techniques can effectively support student performance classification by identifying relationships between input characteristics and educational results.

The adoption of intelligent classification approaches is particularly relevant in higher education, where institutions face challenges related to student retention, personalized learning requirements, and academic resource optimization. Educational institutions require analytical frameworks that not only predict outcomes but also explain the underlying determinants influencing student success.

1.2 Problem Statement

Despite significant advancements in educational analytics, identifying the primary determinants of student achievement remains challenging due to the multidimensional nature of learning performance. Academic success is influenced by interconnected factors including previous educational experiences, learning engagement, technological interaction, and academic support mechanisms. Simple statistical approaches may fail to capture nonlinear relationships among these variables.

Existing educational studies frequently examine isolated aspects of student performance, such as reading ability, technology usage, or dropout behavior. de Oliveira et al. (2008) explored the relationship between reading performance and academic achievement, demonstrating that foundational learning abilities influence educational outcomes. However, higher education environments require broader analytical models capable of integrating multiple determinants simultaneously.

Furthermore, while classification algorithms can identify performance categories, challenges remain regarding model interpretation, adaptability across educational contexts, and effective translation of analytical results into institutional strategies. Therefore, there is a need for an intelligent classification approach that systematically identifies important achievement determinants while maintaining practical relevance for higher education decision-making.

1.3 Research Relevance

The integration of artificial intelligence and educational data mining provides opportunities to move from reactive academic management toward proactive student support systems. By identifying influential achievement factors at an early stage, institutions can implement targeted interventions, improve learning experiences, and allocate academic resources more effectively.

Research on technology-supported learning further demonstrates the importance of digital environments in shaping educational experiences. Matos et al. (2019) analyzed meaningful learning through information and communication technologies (ICTs), highlighting the role of technological resources in improving teaching and learning processes. Such findings indicate that technology-related variables should be considered when developing intelligent classification frameworks for academic achievement.

Similarly, Sendacz et al. (2022) examined technologies and games that motivated individuals to engage in physical activity during the pandemic, demonstrating how digital tools influence behavioral engagement. Although their research focuses on physical activity, it provides broader insight into how technology-mediated environments affect user motivation and participation patterns, which are relevant considerations for educational analytics.

1.4 Research Objectives

This research aims to:

1. Develop a conceptual intelligent classification approach for identifying major determinants influencing student achievement in higher education.
2. Analyze how educational data mining and artificial intelligence techniques contribute to student performance classification.
3. Examine relationships between learner characteristics, technological engagement, and academic outcomes.
4. Identify research gaps and limitations associated with existing classification-based educational analytics approaches.

1.5 Scope and Significance

The scope of this research focuses on intelligent classification methods applied to higher education achievement analysis. The study considers educational data mining principles, artificial intelligence classification strategies, and technology-supported learning factors.

The significance of this research lies in providing a structured perspective for institutions seeking to understand academic success determinants. An effective classification approach can support personalized learning strategies, improve student monitoring systems, and enhance evidence-based educational policies.

2. LITERATURE REVIEW

2.1 Educational Data Mining for Student Profiling and Performance Analysis

Educational data mining has become an essential methodology for discovering hidden patterns within educational datasets. Unlike traditional academic evaluation methods, educational data mining enables institutions to analyze complex relationships among multiple learner characteristics.

Akazaki et al. (2020) investigated educational data mining for identifying candidate profiles, demonstrating how learner characteristics can be systematically analyzed to understand educational populations. Their research highlights the importance of data-driven profiling approaches for recognizing differences among student groups. Such profiling methods provide a foundation for intelligent classification systems because accurate learner categorization depends on identifying meaningful attributes.

Lima and Fagundes (2020) extended the application of educational data mining by investigating factors associated with school dropout in higher education institutions. Their study demonstrates that analytical techniques can identify conditions contributing to negative educational outcomes. The findings emphasize the importance of predictive approaches capable of detecting students requiring additional academic support.

However, existing educational data mining studies often focus on specific outcomes such as dropout prediction rather than comprehensive achievement analysis. A broader classification framework is required to integrate positive academic success indicators with risk-related factors.

2.2 Artificial Intelligence-Based Classification in Education

Artificial intelligence classification techniques provide mechanisms for transforming educational data into predictive categories. These techniques analyze relationships between input variables and predefined outcomes, enabling institutions to classify students according to performance levels.

Yılmaz and Sekeroglu (2020) examined student performance classification using artificial intelligence techniques and demonstrated the potential of machine learning-based approaches in educational prediction. Their research establishes that classification models can support academic decision-making by identifying performance patterns from available data.

The effectiveness of classification approaches depends heavily on the selection of relevant features. Variables representing academic history, learning behavior, and technological interaction must be carefully evaluated to ensure meaningful predictions. Incorrect feature selection may reduce model reliability and limit practical usefulness.

Therefore, intelligent classification approaches should incorporate not only predictive accuracy but also interpretability. Higher education institutions require models that explain why students are classified into specific achievement categories rather than only providing prediction outcomes.

2.3 Technology-Supported Learning and Achievement Factors

Digital technologies have transformed higher education by introducing new forms of interaction, assessment, and knowledge acquisition. Matos et al. (2019) examined ICT-supported meaningful learning and identified the importance of technological integration in educational processes. Their findings suggest that digital learning environments can influence student engagement and knowledge development.

Technology-related factors are particularly relevant for intelligent classification because student interaction with digital platforms can provide measurable behavioral indicators. Learning frequency, resource utilization, and online participation patterns may serve as important classification features.

Sendacz et al. (2022) explored technology-based engagement through a literature review of digital tools and games that encouraged physical activity during the pandemic. Although outside traditional education research, their findings demonstrate how technology can influence motivation and participation behavior. This perspective supports the inclusion of engagement-related variables within broader intelligent analytical frameworks.

2.4 Academic Performance Determinants and Research Gap

Academic achievement is a complex phenomenon influenced by cognitive, behavioral, technological, and institutional factors. de Oliveira et al. (2008) demonstrated that reading ability and academic skills are strongly associated with educational performance, emphasizing the importance of learner capability indicators.

However, current literature reveals several gaps. First, many studies analyze individual factors independently rather than developing integrated classification approaches.

Second, predictive models frequently prioritize accuracy while providing limited explanation of determinant importance. Third, educational contexts differ significantly, making it difficult to apply classification models universally.

The literature indicates a need for intelligent classification frameworks that combine multiple educational dimensions and provide interpretable insights into student achievement. Such approaches can bridge the gap between predictive analytics and practical educational intervention.

3. METHODOLOGY

3.1 Research Design

This study adopts a **conceptual research methodology** based on educational data mining (EDM) and artificial intelligence (AI)-based classification. Rather than evaluating a specific institutional dataset, the methodology develops an intelligent classification framework synthesized from the provided literature to identify the determinants of student achievement in higher education. The framework integrates learner-related, academic, and technology-assisted variables into a structured classification process capable of supporting academic decision-making.

The proposed methodology consists of six interconnected stages: educational data acquisition, data preprocessing, feature identification, intelligent classification, determinant analysis, and decision support. These stages collectively transform raw educational information into actionable insights for educators and institutional administrators.

The methodology is grounded in educational data mining principles discussed by **Akazaki et al. (2020)** and **Lima and Fagundes (2020)**, while the classification mechanism follows the artificial intelligence perspective presented by **Yılmaz and Sekeroglu (2020)**. These studies collectively demonstrate that educational datasets contain meaningful relationships capable of supporting predictive academic analytics. The proposed **Intelligent Classification Approach for Identifying Key Determinants of Student Achievement in Higher Education** extends these concepts into an integrated analytical framework.

3.2 Conceptual Framework

The proposed framework assumes that student achievement is determined by multiple interacting variables rather than a single academic indicator. Four primary categories of determinants are incorporated into the intelligent classification process.

Academic Factors

Academic indicators represent the traditional measures of educational performance. These include previous examination scores, assignment completion, classroom participation, attendance consistency, and continuous assessment results. Academic variables provide the baseline information necessary for evaluating learner progress.

The relationship between reading ability and educational performance reported by **de Oliveira et al. (2008)** supports the inclusion of fundamental academic competencies as important predictive variables.

Student Behavioral Factors

Behavioral characteristics describe how students interact with their learning environment. Examples include study consistency, learning engagement, participation frequency, submission regularity, and interaction with educational resources.

Behavioral indicators frequently explain differences among students with similar academic backgrounds because motivation and engagement influence learning outcomes throughout a semester.

Technology Utilization Factors

Modern higher education increasingly depends on digital learning platforms.

Technology-related determinants include:

- Learning management system usage
- Digital resource access frequency
- ICT-supported learning participation
- Online discussion activity
- Educational software utilization

The importance of ICT-supported learning identified by **Matos et al. (2019)** demonstrates that technology should be considered an essential component of achievement analysis rather than merely an educational supplement.

Institutional Factors

Institutional characteristics also influence achievement outcomes.

Representative variables include:

- Academic advising quality
- Availability of learning resources

- Student support services
- Learning environment
- Educational policies

These variables help explain differences that cannot be attributed solely to learner characteristics.

3.3 Data Preparation

Educational datasets typically originate from multiple independent systems, including examination databases, student information systems, attendance records, and digital learning platforms.

Before classification, collected data undergo several preprocessing stages.

Data Cleaning

Educational datasets often contain:

- Missing values
- Duplicate records
- Inconsistent coding
- Incomplete student profiles

Cleaning ensures that classification algorithms operate using reliable information.

Data Integration

Relevant educational information is merged into a unified dataset.

Integrated variables may include:

- Academic history
- Attendance records
- Digital learning activity
- Assessment performance
- Student demographic identifiers

The integration process creates comprehensive learner profiles suitable for intelligent analysis.

Feature Transformation

Raw educational variables frequently require transformation before classification.

Examples include:

- Normalization of assessment scores
- Categorization of attendance levels
- Encoding qualitative variables
- Scaling numerical attributes

Feature transformation improves analytical consistency across diverse educational indicators.

Table 1. Major Determinants Used in Intelligent Classification

Determinant Category	Representative Variables	Expected Influence
Academic	Grades, assignments, attendance	High
Behavioral	Participation, engagement, study consistency	High
Technology	LMS activity, ICT usage, online interaction	Moderate–High
Institutional	Academic support, learning resources	Moderate

3.4 Intelligent Classification Model

The intelligent classification model consists of sequential analytical stages designed to transform educational information into interpretable student achievement categories.

Stage 1: Input Layer

Student information enters the analytical framework through integrated educational datasets.

Inputs include:

- Academic records

- Technology usage
- Behavioral observations
- Institutional variables

Stage 2: Feature Selection

Not every educational variable contributes equally to prediction accuracy.

Feature selection identifies the variables with the greatest influence on student achievement.

According to **Yılmaz and Sekeroglu (2020)**, effective classification depends largely upon selecting informative predictor variables.

Stage 3: Intelligent Classification

Selected variables are processed using AI-based classification techniques.

The classification stage assigns students into achievement categories such as:

- High Achievement
- Moderate Achievement
- At-Risk
- Low Achievement

The primary objective is not merely prediction but identification of influential determinants responsible for classification outcomes.

The **Intelligent Classification Approach for Identifying Key Determinants of Student Achievement in Higher Education** emphasizes interpretability alongside predictive capability so that institutional stakeholders can understand the reasons underlying classification decisions.

Stage 4: Determinant Ranking

Following classification, influential variables are ranked according to their contribution.

Example ranking:

1. Attendance consistency
2. Assignment completion
3. LMS participation
4. Previous academic performance
5. Student engagement

Ranking allows institutions to prioritize interventions where they will produce the greatest educational benefit.

Stage 5: Decision Support

Classification outcomes support educational decisions including:

- Early academic intervention
- Personalized learning plans
- Student mentoring
- Resource allocation
- Performance monitoring

The final stage converts analytical results into practical institutional actions.

Figure 1. Proposed Intelligent Classification Framework

Educational Data Sources

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Data Cleaning & Integration

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Feature Engineering

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Feature Selection

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AI-Based Classification

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Achievement Categories

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Determinant Ranking

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Decision Support System

3.5 Analytical Workflow

The methodology follows an iterative workflow.

Initially, educational information is collected from institutional sources.

After preprocessing, variables undergo feature engineering to improve analytical quality.

Selected variables are then supplied to the intelligent classification module.

Classification outcomes are evaluated to identify influential determinants affecting academic achievement.

Finally, ranked determinants support institutional planning and personalized interventions.

This workflow enables continuous refinement as additional educational information becomes available.

3.6 Theoretical Foundation

The proposed methodology integrates three complementary theoretical perspectives.

The first perspective is educational data mining, emphasizing extraction of meaningful educational knowledge from institutional datasets (**Akazaki et al., 2020; Lima & Fagundes, 2020**).

The second perspective is artificial intelligence-based classification, which categorizes learners according to multidimensional educational characteristics (**Yılmaz & Sekeroglu, 2020**). The **Intelligent Classification Approach for Identifying Key Determinants of Student Achievement in Higher Education** adopts this perspective as its central analytical mechanism.

The third perspective emphasizes technology-supported learning environments. Studies by **Matos et al. (2019)** and **Sendacz et al. (2022)** indicate that digital engagement represents an increasingly important determinant of learner behavior and educational participation.

Together, these perspectives establish a comprehensive theoretical basis for intelligent academic analytics.

3.7 Methodological Strengths

The proposed methodology offers several advantages.

It integrates academic, behavioral, technological, and institutional determinants within a unified analytical framework instead of examining isolated variables.

The approach emphasizes interpretability, enabling educators to understand why students belong to particular achievement categories rather than receiving only prediction results.

The modular design also permits adaptation across different higher education institutions with varying educational datasets.

Finally, the methodology supports evidence-based academic decision-making by transforming educational data into meaningful institutional knowledge.

4. RESULTS

The proposed intelligent classification approach demonstrates that student achievement in higher education is influenced by a combination of academic, behavioral, technological, and institutional determinants rather than by isolated performance indicators. The conceptual framework indicates that integrating these variables within an educational data mining environment provides a more comprehensive understanding of learner performance than traditional grade-based assessment.

Analysis of the reviewed studies suggests that academic variables remain the strongest predictors of achievement; however, their predictive capability improves substantially when combined with behavioral and technology-related indicators. Academic performance, attendance consistency, assignment completion, and reading competency collectively establish the foundation for learner classification. The relationship between reading ability and educational performance identified by **de Oliveira et al. (2008)** reinforces the importance of core academic competencies in determining student success.

Educational data mining studies further demonstrate that learner profiling enables institutions to distinguish meaningful differences among students with comparable academic records. The profiling approach presented by **Akazaki et al. (2020)** indicates that multidimensional educational data reveal hidden characteristics that conventional evaluation methods frequently overlook. Such findings support the inclusion of multiple learner attributes within intelligent classification systems.

Artificial intelligence-based classification contributes significantly to predictive educational analytics by identifying complex relationships among variables that are difficult to detect through conventional statistical approaches. The classification methodology discussed by **Yılmaz and Sekeroglu (2020)** illustrates that AI techniques improve categorization accuracy while facilitating early identification of students requiring academic intervention. Consequently, the proposed framework emphasizes both predictive capability and interpretability so that educational stakeholders can understand the determinants influencing classification outcomes.

Technology-related variables also emerge as influential determinants of academic achievement. Student engagement with digital learning platforms, educational resources, and ICT-supported instructional environments provides measurable behavioral indicators that complement traditional academic variables. The work of **Matos et al. (2019)** demonstrates that meaningful learning experiences are strengthened through effective ICT integration, while **Sendacz et al. (2022)** illustrate that digital technologies positively influence user engagement and participation. These findings support the inclusion of technology utilization metrics within intelligent educational classification models.

The review additionally identifies institutional support mechanisms as indirect contributors to academic achievement. Academic advising, learning resources, and educational support services influence student engagement and learning continuity, particularly among students experiencing academic difficulties. Although these variables may not independently determine achievement, they strengthen the predictive capacity of integrated classification models.

Overall, the findings indicate that intelligent classification systems provide greater analytical value when they combine heterogeneous educational variables rather than relying exclusively on examination scores or cumulative grade point averages. Such multidimensional approaches improve institutional capability to identify achievement determinants, prioritize interventions, and support personalized learning strategies.

Table 2. Summary of Major Findings

Analytical Aspect	**Key Finding**	**Educational Implication**
Academic Variables	Strong predictors of achievement	Support continuous academic monitoring
Behavioral Indicators	Improve prediction when combined with academic data	Enable early intervention strategies
Technology Utilization	Enhances learner engagement analysis	Supports digital learning optimization
Educational Data Mining	Reveals hidden learner patterns	Improves institutional decision-making
AI-Based Classification	Produces accurate learner categorization	Facilitates personalized academic support
Integrated Framework	Provides comprehensive achievement analysis	Supports evidence-based educational policies

5. DISCUSSION

The findings demonstrate that intelligent classification represents a significant advancement over conventional approaches to student performance evaluation. Traditional assessment methods primarily emphasize academic outcomes after learning has occurred, whereas intelligent classification enables proactive identification of factors contributing to future achievement. This shift from descriptive evaluation toward predictive educational analytics enhances institutional capacity for timely academic intervention.

Educational data mining forms the analytical foundation of the proposed framework by enabling systematic exploration of educational datasets. The learner profiling strategy discussed by **Akazaki et al. (2020)** illustrates that student populations contain diverse behavioral and academic characteristics that require multidimensional analysis. Similarly, the dropout-related investigation conducted by **Lima and Fagundes (2020)** highlights the value of predictive educational analytics for identifying learners requiring additional institutional support. Together, these studies reinforce the importance of integrating educational data mining techniques into higher education decision-support systems.

Artificial intelligence classification further strengthens educational analytics by identifying nonlinear relationships among determinants that may not be observable through conventional statistical methods. The research by **Yılmaz and Sekeroglu (2020)** demonstrates that AI-based classification improves learner categorization and prediction accuracy. However, predictive accuracy alone is insufficient for educational decision-making. Institutions require transparent analytical processes capable of explaining why students are classified into particular achievement categories. Consequently, interpretability should be considered an essential characteristic of intelligent educational models.

Technology-supported learning also represents an increasingly influential component of academic achievement analysis. The integration of ICT into educational practice, as discussed by **Matos et al. (2019)**, suggests that digital engagement provides valuable behavioral information reflecting student participation and learning commitment. Likewise, **Sendacz et al. (2022)** demonstrate that technology-enhanced environments can positively influence motivation and participation, indicating that digital interaction metrics possess analytical value beyond simple usage statistics.

Despite these strengths, several limitations remain. Educational institutions differ considerably regarding curriculum design, technological infrastructure, learner demographics, and assessment methodologies. Consequently, classification models developed for one institution may require adaptation before implementation in another educational context. Data quality also represents a significant challenge because missing records, inconsistent documentation, and incomplete learner profiles may reduce classification reliability.

Another limitation concerns ethical considerations associated with educational analytics. Classification outcomes should complement professional academic judgment rather than replace educator decision-making. Incorrect interpretation of predictive results may lead to inappropriate interventions or unintended learner labeling. Therefore, intelligent classification should function as a decision-support mechanism that assists educators while maintaining transparency and fairness.

Overall, the proposed framework contributes a balanced perspective by integrating educational data mining, artificial intelligence classification, and technology-supported learning into a unified analytical model capable of supporting evidence-based academic management.

6. CONCLUSION

This research presented an **Intelligent Classification Approach for Identifying Key Determinants of Student Achievement in Higher Education** by synthesizing concepts from educational data mining, artificial intelligence-based classification, and technology-supported learning. The review demonstrates that student achievement is influenced by multiple interconnected determinants, including academic performance, behavioral engagement, technology utilization, and institutional support mechanisms.

The proposed framework extends existing educational analytics by integrating diverse determinants into a structured classification process emphasizing both predictive capability and interpretability. Unlike conventional performance evaluation methods, the framework enables institutions to identify influential achievement factors, categorize learners according to educational needs, and support evidence-based intervention strategies.

The study also highlights the importance of educational data quality, feature selection, and model transparency for successful implementation of intelligent classification systems. While predictive analytics provides valuable institutional insights, classification outcomes should be interpreted within broader educational contexts to ensure responsible and equitable academic decision-making.

Future research may validate the proposed conceptual framework using real-world institutional datasets, compare alternative classification algorithms, investigate explainable artificial intelligence techniques for educational analytics, and evaluate longitudinal student achievement patterns across diverse higher education environments.

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