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Predicting Student Outcomes in Open High Schools Using Educational Data Mining

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Abstract

Open high schools fulfill a critical function by offering flexible educational pathways for students encountering diverse socioeconomic and personal challenges. Nevertheless, escalating dropout rates represent a significant concern, necessitating robust predictive models to facilitate early interventions. This study employed educational data mining (EDM) techniques to analyze the academic trajectories of 484,158 students enrolled in Turkish open high schools. We evaluated multiple classification algorithms—J48, decision tree, k-nearest neighbors (kNN), naïve Bayes, and random forest—across four distinct data preprocessing scenarios to predict student status (dropout/delayed graduation/graduation). The J48 algorithm demonstrated superior performance, achieving an accuracy of 80.47% and a kappa statistic of 0.61. Key findings reveal that academic and administrative features, notably total credit accumulation and initial enrollment type, are more important predictors than demographic variables. This research provides empirically grounded insights for the early identification of at-risk students. It offers data-driven recommendations to enhance student retention policies within open high school systems, contributing a large-scale, multi-class prediction analysis within a unique, under-researched national distance education context.

Keywords: educational data mining, dropout prediction, open high school, machine learning, distance education, student retention, early warning system

Introduction

Education is fundamental to human development, influencing individual opportunities and societal progress. The United Nations' (UN) 2030 Sustainable Development Goals reflect this priority, targeting universal primary and secondary access, vocational skills development, and equitable tertiary education (United Nations Department of Economic and Social Affairs [UNDESA], 2015), while the UN Human Development Index measures educational progress through average and expected years of schooling (United Nations Development Program [UNDP], 2021). As a UN member, Türkiye pursues these educational aims, yet faces persistent challenges in achieving these targets.

Equitable access to quality education remains a significant challenge in Türkiye (Ministry of National Education [MoNE], 2015). Although overall schooling rates vary across educational levels—68% in preschool, 91% in primary, 84% in secondary, and 44% in higher education (MoNE, 2019)—secondary education, in particular, exhibits notable regional disparities. For instance, the secondary school enrollment rate is 91% in western Anatolia, compared to 72% for males and 68% for females in southeastern Anatolia (MoNE, 2019). Furthermore, among adults aged 25–34, nearly half have not completed secondary education, with a significant gender gap in average years of schooling: 7.3 years for women versus 9 years for men (Organisation for Economic Co-operation and Development [OECD], 2018; UNDP, 2021).

Addressing educational challenges, Türkiye extended compulsory education to 8 years (Türkiye Cumhuriyeti Resmî Gazete [TC Resmî Gazete], 1997), then 12 years (TC Resmî Gazete, 2012). National development plans promoted open and distance education for equality and lifelong learning (TC Resmî Gazete, 2006, 2013). Subsequently, open high school (OHS) enrollment grew from 14% (940,268) of all secondary students in 2012 to 26% (1,554,938) in 2017 (MoNE, 2012, 2017). However, dropout rates increased dramatically; by 2017, OHS dropouts (N = 2,143,674) reached 137% of active enrollment (Polat, 2021), a persistence problem recognized in MoNE strategic planning (2015).

Secondary education dropout impacts national development through diminished human capital (Rosenzweig, 2010; Rumberger, 2020), reduced productivity (Aydın et al., 2012; Çalışkan et al., 2013), and increased social costs in crime, health, and life expectancy (Ereş, 2005; Kızmaz, 2004; Luy et al., 2019). Young adults without high school diplomas face higher unemployment rates (OECD, 2021). Parental education also significantly influences academic outcomes across generations (MoNE, 2022). Student dropout within Turkish OHSs represents an escalating problem affecting a student demographic facing socioeconomic and personal barriers to traditional schooling and reducing OHS dropout rates is thus crucial for both individual success and the country's socioeconomic advancement.

Open High Schools in Türkiye

Türkiye's first OHS (in Turkish, açık öğretim lisesi or AÖL) was established in 1992. Subsequently, the vocational open high school (in Turkish, mesleki açık öğretim lisesi or MAÖL) was established in 2006, followed by the open education imam hatip high school (açık öğretim imam hatip lisesi or AÖİHL) in 2016. While these institutions were initially part of AÖL, they later became separate entities. As of the 2020/2021 academic year, the total number of actively enrolled students across these OHSs reached 1,452,331 (MoNE, 2021).

Despite the size of the student population, research on the OHS dropout problem remains limited. Early studies focused on operational aspects, learning environments, materials, and support services

(Demiray & Sağlık, 2003). Later research examined reasons for transferring to open schools (Adıgüzel, 2016; Çuhadar Öncü, 2017; Şahin, 2017), student-perceived obstacles (Çiçek, 2005; Şahin, 2017; Sipahi, 2019; Soylu, 2014), academic achievement (Özkahveci, 2001), service effectiveness (Bedel, 2006; Sarıhan, 2010; Şentürk, 2009; Yavuz, 2014), student perspectives (Demirtaş et al., 2017; Dere, 2002), and individual differences (Randler et al., 2014).

However, much of this existing research is descriptive and localized, relies on small sample sizes (often focusing on MAÖL students due to face-to-face components), and lacks representativeness concerning the vast and diverse population enrolled across Türkiye. Consequently, there is limited understanding of the factors predicting persistence or dropout on a national scale, hindering the development of evidence-based interventions. While engaging large, representative samples present logistical challenges (labor, time, cost), the increasing availability of rich administrative data within student information systems offers a valuable opportunity. Educational data mining (EDM) techniques can leverage this data to uncover complex patterns and predictors of student outcomes that might otherwise remain obscured.

Educational Data Mining

Information technology advancements enable educational institutions to collect comprehensive student data through sophisticated management systems, creating valuable analytical opportunities. Data mining, extracting implicit and potentially useful information from large datasets (Han et al., 2011), provides tools for addressing complex educational challenges. EDM applies these methods to large-scale educational data, illuminating student behaviors and learning environments (International Educational Data Mining Society, n.d.). EDM applications primarily focus on predicting academic performance, identifying at-risk students, and understanding dropout factors (Romero & Ventura, 2010).

EDM holds promise for anticipating educational needs, personalizing learning experiences, and ultimately improving student outcomes. Prediction studies, a core component of EDM, assist educators in identifying critical success factors and their interrelationships, thereby highlighting areas for targeted intervention and systemic improvement. Within the Turkish context, the concurrent rise in demand for OHSs and the alarming increase in dropout rates create a compelling case for applying EDM. The existing research gap concerning dropout predictors in these specific institutions necessitates the use of data mining methods to uncover potentially complex patterns associated with success, delayed graduation, and dropout, with the ultimate goal of enhancing completion rates.

Identifying students at risk of dropout is a crucial prerequisite for implementing timely and effective interventions (Dekker et al., 2009; Heppen & Therriault, 2008; Márquez-Vera et al., 2016; Tanner, 2003). Dropout is a multifaceted phenomenon influenced by individual, academic, family, school, and community factors (Rumberger & Lim, 2008). However, collecting comprehensive data, particularly psychosocial or detailed background information, via traditional methods such as surveys is often impractical in large-scale distance education settings like Turkish OHSs. Therefore, leveraging readily available administrative data from student information systems presents a pragmatic and efficient approach to investigating dropout predictors, conserving resources while enabling analysis at scale.

A review of the EDM literature focused on predicting student performance and dropout reveals a predominant focus on higher education settings (Berens et al., 2019; Delen, 2010; Djulovic & Li, 2013; Kovacic, 2010; Lassibille & Navarro-Gomez, 2008). Studies examining dropout at the high school level are comparatively scarce (Lee & Chung, 2019; Márquez-Vera et al., 2013; Şara et al., 2015). Existing research spans diverse national contexts, educational systems (face-to-face, distance, e-learning), and data sources. While common predictors such as academic achievement (GPA, prior grades, exam scores), personal characteristics (gender, age, disability), and sometimes psychometric traits (motivation) emerge, the heterogeneity in study contexts, methodologies, sample sizes, and data types limits the generalizability of findings. This variability underscores the necessity for context-specific research.

This study is conceptually grounded in established models of student departure, primarily drawing upon Tinto's (1975) model of student integration, and Bean and Metzner's (1985) model tailored for non-traditional students. Tinto's framework emphasizes the critical roles of academic and social integration in fostering persistence. Bean and Metzner's model, particularly relevant to the OHS population, which often includes non-traditional learners, additionally highlights the influence of external environmental factors (e.g., employment, family responsibilities) alongside academic variables and background characteristics. This theoretical lens guides our variable selection, positing that a combination of factors—including academic progress (e.g., credits earned), background characteristics (e.g., enrollment type, age), and potentially external factors reflected in administrative data (e.g., employment status)—interact to shape student persistence within the unique context of OHSs.

Given research gaps—the lack of national-scale studies in the Turkish OHS context, the limited focus on the dropout problem in open secondary education, and the need for nuanced outcome prediction—an EDM study investigating dropout in this specific setting is warranted. Such research is essential not only for addressing existing knowledge gaps but also for guiding future research directions and informing the development of targeted, evidence-based policies and interventions aimed at improving student retention. This study directly addressed these gaps by applying predictive modeling to a comprehensive, nationwide dataset of Turkish OHS students, employing a multi-class outcome variable for a more nuanced and realistic representation of learner trajectories, and identifying the most important predictors specific to this unique distance secondary education environment.

Research Questions

This study aimed to predict the status (graduation, active/delayed graduation, or dropout) of students enrolled in Turkish OHSs at the end of their standard 4-year education period (defined as the official program duration starting from the student's initial enrollment date), using EDM methods applied to data available within the institutional student information system. In pursuit of this aim, the study posed the following research questions:

> RQ1: What is the classification performance of various machine learning models developed to predict the graduation, dropout, and active/delayed status of OHS students?
>
> RQ2: Which student features available in the administrative dataset are the most important predictors of these outcomes?

Methodology

Employing EDM techniques to analyze educational datasets, this study followed the Cross Industry Standard Process for Data Mining (CRISP-DM) model (Chapman et al., 2000), a structured framework guiding the analysis from business understanding through deployment (Figure 1). This systematic methodology facilitated a rigorous approach to the data analysis process.

Data Analysis

Following the CRISP-DM framework, all data processing and modeling were carried out using RapidMiner Studio VM software (Version 9.0), a comprehensive data science platform facilitating visual workflow design and automation across the data science lifecycle (Altair Engineering, 2026).

Business Understanding

The core objective was predicting student status after the standard 4-year timeframe, with three target categories:

- graduated: students who completed all requirements and received their diploma within or by the end of the 4-year timeframe.
- active/delayed graduation: students who remained enrolled beyond the standard 4 years, indicating delayed progress towards graduation.
- dropout: students who discontinued their studies and were no longer enrolled, without having graduated.

Figure 1

CRISP-DM Model

Note. From *CRISP-DM Process Diagram,* by K. Jensen, 2012, Wikimedia Commons (https://commons.wikimedia.org/w/index.php?curid=24930610). CC BY-SA 3.0.

Data Understanding

The dataset was obtained with official permission from the MoNE Information Processing Department (Official Letter No: 65968543-605.01-E.86777), adhering to MoNE regulations. It comprised anonymized records for students who first enrolled in one of the three types of OHSs (AÖL, MAÖL, or AÖİHL) during the 2013 academic year. This year was chosen as it marked the implementation of 12-year compulsory education and saw a significant increase in OHS enrollment. The final analysis dataset, after handling exclusions for specific non-representative cases (e.g., deceased, returned to formal education), consisted of 484,158 student records.

The raw data contained various administrative, demographic, and academic features. Exploratory analysis using RapidMiner identified the potentially relevant attributes listed in Table 1.

Table 1

Features Initially Available in the Dataset

Category	Feature	Description
Administrative	School type	Type of OHS (AÖL/MAÖL/AÖİHL)
	Enrollment type	Educational status at enrollment (e.g., primary/secondary graduate, transfer from traditional HS)
	Field/department	Registered field or department (if applicable)
Demographic	Date of birth	Student's date of birth
	Gender	Student's gender
	Address city	City of residence
	Address district	District of residence
	Employment status	Employment status (employed/unemployed, type of employment)
	Disability status	Presence and type of disability
	Special status	Special circumstances (e.g., detained, child of a martyr/veteran, under court order)
	Military service	Military service status (relevant primarily for males)
Academic	Status	Target variable: Student's status (graduated, active, dropout)
	Previous system	The class transition system of the school student transferred from
	Previous school	Type of school transferred from (if applicable)
	Total credit count	Total course credits earned by the student

Note. OHS = open high school; AÖL = açık öğretim lisesi [open high school]; MAÖL = mesleki açık öğretim lisesi [vocational open high school]; AÖİHL = açık öğretim imam hatip lisesi [imam hatip open high school].

The majority of students (80%) were enrolled in AÖL, followed by MAÖL (13%) and AÖİHL (7%). Gender distribution varied by school type: we found approximately 60% were male in the AÖL, 62% were male in the MAÖL, whereas 63% were female in the AÖİHL.

Data Preparation

Several steps were taken to prepare the data for modeling:

- An age feature at the time of enrollment (calculated from date of birth) was added, aligning with theoretical propositions regarding the impact of age on student persistence.

- A region feature was derived using the European Union's nomenclature of territorial units for statistics (NUTS) level 1 classification (Eurostat, 2026) based on the address city to capture regional socioeconomic variations that might influence educational outcomes.

- The status feature was designated as the target variable. The distribution across the three classes was: graduated 11.1%, active/delayed graduation 26.2%, and dropout 62.7%.

The dataset exhibited significant class imbalance. We deliberately avoided resampling techniques to preserve the authentic data distribution reflecting the real-world phenomenon. Our strategy focused on using algorithms relatively robust to imbalance and employing evaluation metrics (precision, recall, F-measure, kappa) less sensitive to imbalance than simple accuracy (He & Garcia, 2009).

To systematically evaluate data representation impact on model performance, we implemented four progressive preprocessing stages: stage 1: minimal transformation; stage 2: removal of high-missingness features; stage 3: simplification of nominal features; and stage 4: discretization of continuous variables.

Modeling

Five classification algorithms were selected for this study: decision tree, J48, k-nearest neighbors (kNN), naïve Bayes, and random forest. These algorithms were chosen because they represent different methodological approaches to classification and have demonstrated effectiveness in EDM research (Kılınç, 2015; Shahiri & Husain, 2015; Umar, 2016; Yukselturk et al., 2014; Yurdakul, 2015). Testing multiple algorithms allowed us to identify which approach performed best for predicting student outcomes in the Turkish OHS context.

The selected algorithms operate using the following distinct methodologies:

- decision tree: constructs a flowchart-like model where branches represent decision nodes derived from specific student characteristics, such as credit accumulation.

- J48: an advanced decision tree that improves prediction by automatically pruning (trimming) unnecessary branches to prevent overfitting, when a model learns training data too specifically and performs poorly on new data. J48 works by examining student features, selecting the feature that best separates students into outcome groups, creating branches, and pruning branches that don't improve accuracy.

- random forest: generates an ensemble of decision trees and aggregates their predictions through a voting process to increase accuracy.

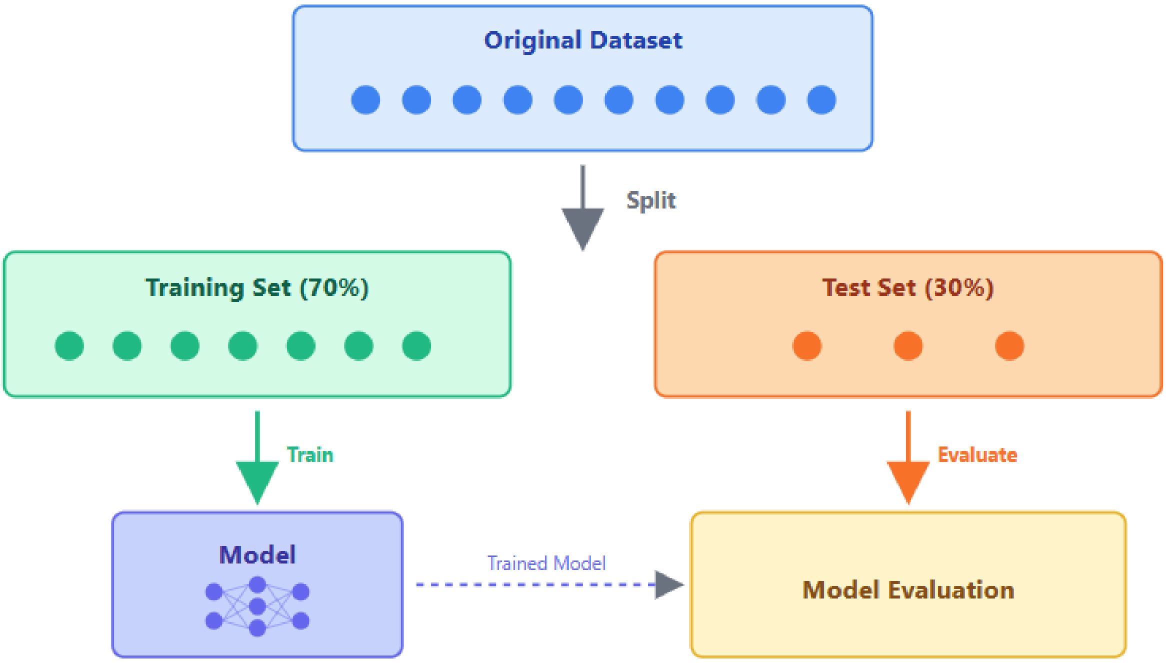
- k-nearest neighbors (kNN): uses instance-based learning, classifying students by identifying the prevailing outcome among similar data points.

- naïve Bayes: applies probabilistic principles to predict outcomes based on attribute likelihoods and the assumption of feature independence.

For model training and testing, the holdout method (70% training, 30% testing), depicted in Figure 2, was employed with stratified sampling, which builds random subsets to ensure the class distribution is the same as in the whole dataset (Altair Engineering, 2026).

Figure 2

Holdout Method Used for Model Training and Testing



All algorithms were run using their default parameter settings (without fine-tuning) within RapidMiner Studio (Altair Engineering, 2026). This approach was chosen to establish a baseline comparison of algorithm performance under standard conditions across different preprocessing stages (Romero & Ventura, 2020), rather than optimizing each algorithm individually, which was considered beyond the scope of this initial investigation but represents an avenue for future refinement (Witten et al., 2016).

Evaluation

Model performance was assessed using standard metrics derived from the confusion matrix on the test set (Hossin & Sulaiman, 2015): correct classification rate (CCR/accuracy), precision, recall (sensitivity), F-measure (F1-score), and kappa statistic (Cohen, 1960; Landis & Koch, 1977). Model performance metrics are explained in Figure 3, which also shows the confusion matrix from which we derived these metrics. (Further detail about this matrix is presented in Table 2).

Figure 3

Model Performance Metrics

Accuracy (CCR)

Percentage of all correct predictions

Example: 80 correct out of 100 students = 80% accuracy

Precision

When model predicts an outcome, how often is it correct?

Example: Predicted "Graduated" 20 times, 18 actually graduated = 90% precision

Recall (Sensitivity)

Of all students with an outcome, how many did model identify?

Example: 25 actually graduated, model found 20 of them = 80% recall

F-Measure (F1-Score)

Balance between Precision and Recall (harmonic mean)

Single metric combining both: 85% F-measure = good balance

Kappa Statistic

Performance compared to random guessing

Interpretation Scale:

≤ 0.00: No better than chance
0.01-0.20: Slight agreement
0.21-0.40: Fair agreement
0.41-0.60: Moderate agreement
0.61-0.80: Substantial agreement
0.81-1.00: Almost perfect

Confusion Matrix Example:

Actual \ Predicted	Dropout	Graduated	Active
Dropout	82,182	50	18,101
Graduated	634	15,459	2,112
Active	6,651	306	17,123

Correct predictions
Incorrect predictions

Using multiple metrics provides a comprehensive view of model performance. A model might achieve high CCR but low recall for a particular class, meaning it is correct most of the time but misses many cases of that outcome. In the Turkish OHS context, the ideal model would be one that not only achieves high overall CCR but also reliably identifies at-risk students (high recall for the dropout class) without excessive false alarms (high precision). By evaluating models across multiple metrics, we were able to identify which algorithm provided the best balance of performance characteristics for the specific goal of predicting student outcomes.

Deployment

This phase involved reporting the findings, discussing their implications, and formulating recommendations, as presented below.

Findings

The classification analyses were performed iteratively across the four preprocessing stages:

- stage 1: initial modeling using most available features with minimal transformation (baseline).
- stage 2: removal of features with high percentages of missing values or limited applicability (e.g., the features previous school, previous system, and military service status) to create a more complete and potentially robust dataset.
- stage 3: transformation and simplification of nominal features. For example, employment status and disability status were binarized (yes/no). Categories within enrollment type were consolidated. The region feature replaced detailed location data. This stage aimed to reduce complexity and potentially improve model generalizability.
- stage 4: discretization of continuous variables (age, total credit count) using different binning strategies (frequency-based, range-based) and varying numbers of bins (2, 4, 8). This explored whether converting continuous features into categorical ones improved performance for certain algorithms.

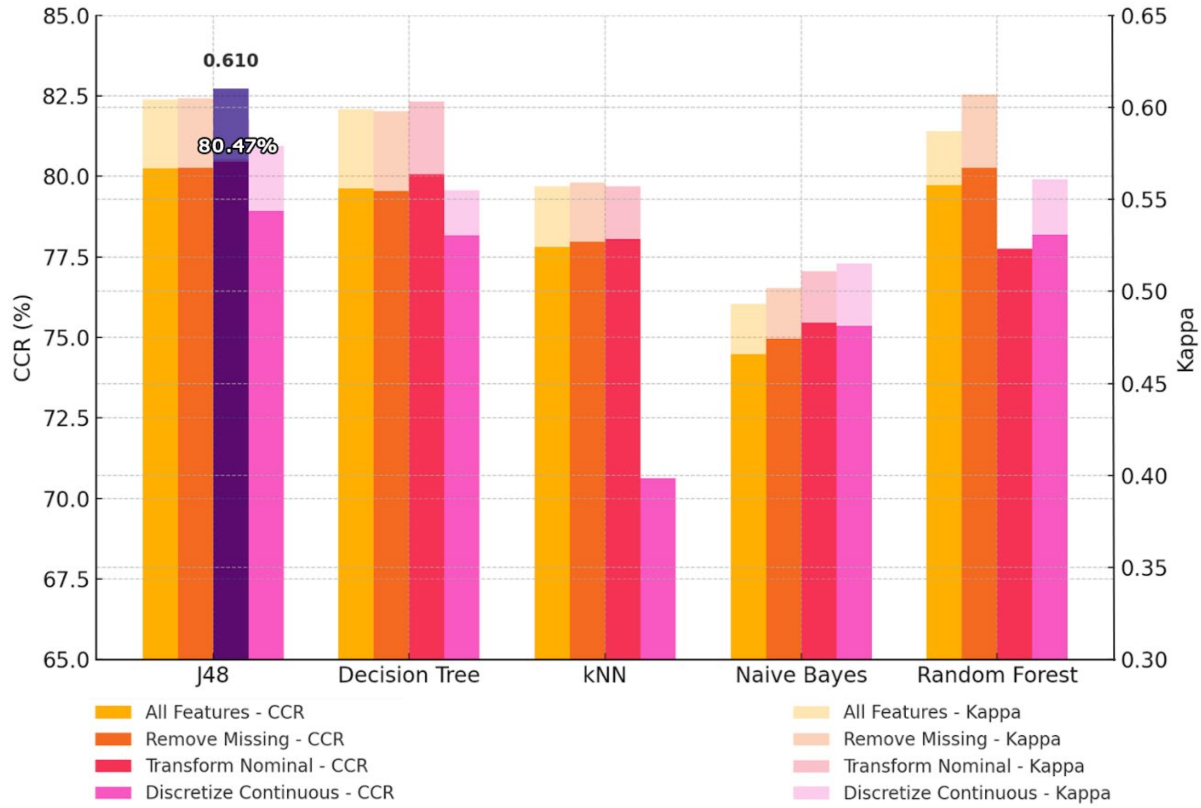
The performance of the five selected algorithms was evaluated at each stage using the test dataset.

Model Performance Comparison

The CCR and kappa metrics for the models developed using the aforementioned datasets are presented in Figure 4.

Figure 4

Comparison of Algorithm Performance Across Preprocessing Stages



Note. The purple bar highlights the most accurate algorithm, J48, and its performance metrics. CCR = correct classification rate.

Analysis across preprocessing stages showed accuracy (CCR) ranging from 73.36% to 80.47%. The highest performance was consistently achieved after the third preprocessing stage (simplifying nominal features). Within this stage, the J48 algorithm yielded the best results, achieving a CCR of 80.47% and a Kappa statistic of 0.61. This kappa value indicates substantial agreement (Landis & Koch, 1977), suggesting a robust model performing significantly better than chance.

Detailed Performance of the Best Model (J48—Stage 3)

The confusion matrix for the J48 model, the best performing on the test set (shown earlier in Figure 3), is presented in Table 2.

Table 2

Confusion Matrix for the J48 Model (N Instances in Test Set)

	Predicted			Total actual	Recall, %
	Dropout	Graduated	Active		
Actual					
Dropout	82.182	50	18.101	100.333	91.5
Graduated	634	15.459	2.112	18.205	97.7
Active	6.651	306	17.123	24.080	45.8
Total Predicted	89.467	15.815	37.336	142.618	
Precision, %	90.1	88.2	63.5		

The model demonstrates excellent performance for dropout and graduated classes (recall > 91.5%). Performance is notably lower for the active/delayed graduation class, particularly recall (45.8%). This difficulty in identifying students persisting beyond four years warrants further discussion.

The overall performance metrics for the best J48 model are shown in Table 3.

Table 3

Overall Performance Metrics for the Best J48 Model

Algorithm	Weighted avg recall, %	Weighted avg precision, %	Weighted avg F-measure, %	CCR, %	Kappa
J48	78.48	79.31	78.89	80.47	0.61

Note. CCR = correct classification rate.

These balanced overall metrics indicate a robust model that performed consistently across different facets of classification, minimizing bias toward predicting one class at the expense of others (Ben-David, 2008). This level of performance aligns well with benchmarks often considered effective for practical application in educational settings (Baker & Inventado, 2014; Romero & Ventura, 2010).

Feature Importance

Feature importance analysis for the best J48 model (Stage 3 data) revealed the relative importance of predictors (Figure 5).

Figure 5

Feature Importance Weights for the Best J48 Model

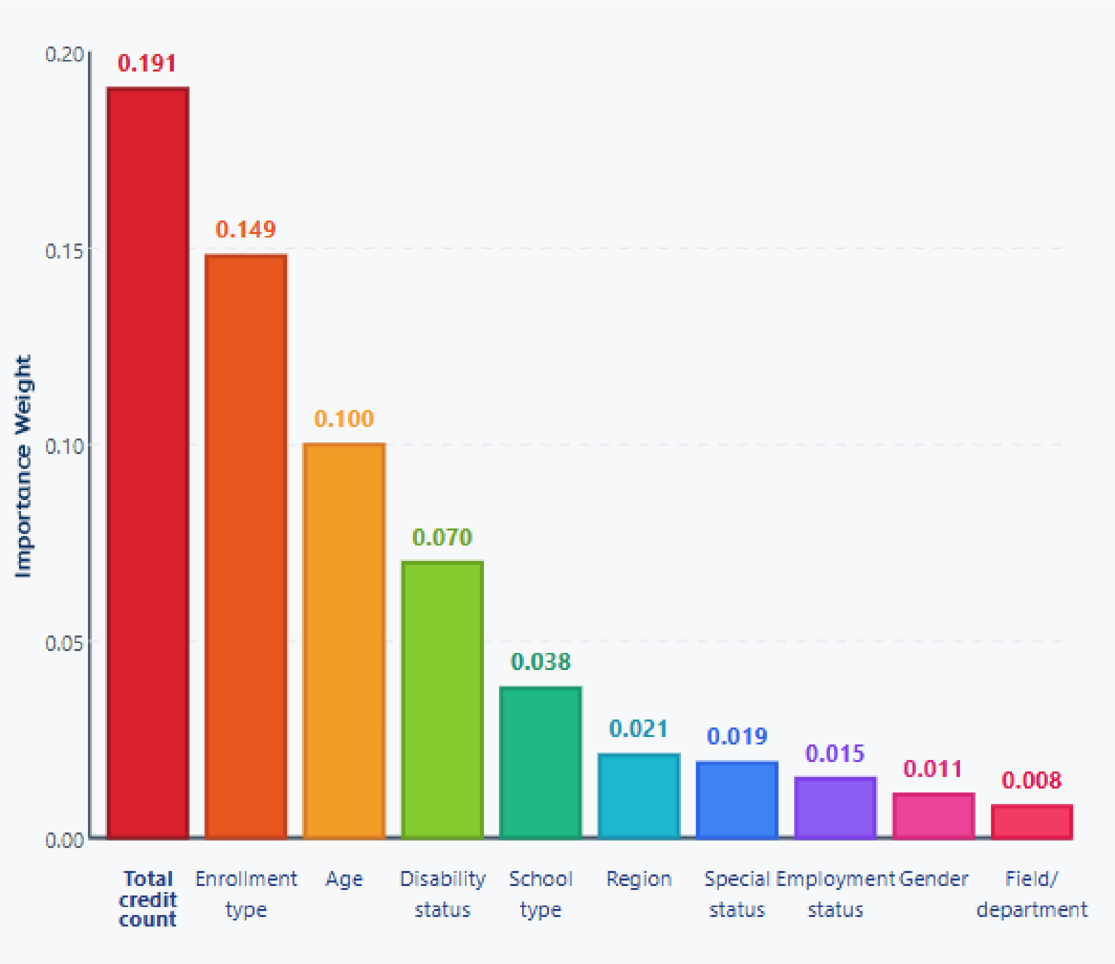


Figure 5 presents the feature importance weights, revealing each predictor's contribution to model performance. Academic progress indicators (total credit count, enrollment type) demonstrate greater predictive power than demographic variables.

Interpretation of Decision Rules

The J48 algorithm generated a complex decision tree (2,832 branches, 2,045 leaves) expressible as IF-THEN rules. A section from the tree structure of the J48 model is given in Figure 6.

Figure 6

A Section From the Tree Structure of the J48 Model

```
TOTALCREDIT > 48
|   REGISTRATION_TYPE = PRIMARY_SCHOOL_GRADUATE
|   |   TOTALCREDIT <= 91
|   |   |   AGE <= 18: ACTIVE (3693.0/941.0)
|   |   |   AGE > 18
|   |   |   |   TOTALCREDIT <= 66
|   |   |   |   |   FIELD/DEPARTMENT = NONE
|   |   |   |   |   |   AGE <= 19: ACTIVE (418.0/151.0)
|   |   |   |   |   |   AGE > 19
|   |   |   |   |   |   |   SCHOOL_TYPE = OPEN HIGH SCHOOL
|   |   |   |   |   |   |   WORKING = NO
|   |   |   |   |   |   |   SPECIAL_STATUS = NONE
|   |   |   |   |   |   |   |   REGION = TRNC: DROPOUT (1.0)
|   |   |   |   |   |   |   |   REGION = TRC: DROPOUT (599.0/235.0)
|   |   |   |   |   |   |   |   REGION = TRB
|   |   |   |   |   |   |   |   |   GENDER = FEMALE
|   |   |   |   |   |   |   |   |   |   TOTALCREDIT <= 64: DROPOUT (154.0/48.0)
|   |   |   |   |   |   |   |   |   |   TOTALCREDIT > 64: ACTIVE (26.0/11.0)
|   |   |   |   |   |   |   |   |   GENDER = MALE
|   |   |   |   |   |   |   |   |   |   AGE <= 29: ACTIVE (52.0/18.0)
|   |   |   |   |   |   |   |   |   |   AGE > 29: DROPOUT (42.0/11.0)
|   |   |   |   |   |   |   |   REGION = TRA
|   |   |   |   |   |   |   |   |   GENDER = FEMALE: ACTIVE (70.0/32.0)
```

While the full tree is impractical to display, representative rules highlight the model's logic as shown in Figure 7.

Figure 7

IF-THEN Decision Rule Examples of the J48 Model

These examples show the model combining multiple features, with total credit count often serving as a primary splitting criterion, reflecting its high importance.

Conclusion and Discussion

This study employed EDM classification analysis on a large dataset (N = 484,158) to predict the end-of-term status of students in Turkish OHSs. Departing from common binary classifications, this research's three-class approach (graduated, active, dropped out), despite complexities such as imbalance, offers a more nuanced representation of learner trajectories, contributing to an underdeveloped EDM area (Martins et al., 2023).

Following the CRISP-DM framework, we applied data transformation and manual feature selection to a dataset containing demographic, academic, and administrative features. Multiple classification algorithms were evaluated, acknowledging that no single algorithm is universally superior. The J48 algorithm emerged as the most effective, achieving an 80.47% correct classification rate (CCR) and a kappa value of 0.61, accurately predicting the status for four out of five students in the test set. This performance is notable given the three-class complexity and surpasses many binary classification studies. While J48 often performs well in EDM (Al-Barrak & Al-Razgan, 2016; Dekker et al., 2009; Kabakchieva, 2013; Kumar & Vijayalakshmi, 2011; Mishra et al., 2014; Sumitha & Vinothkumar, 2016), other algorithms such as random forest (Şara et al., 2015), approximate nearest neighbor (Ibrahim & Rusli, 2007), support vector machine (Delen, 2010), and k nearest neighbors (Yukselturk et al., 2014) have shown better results in specific contexts, likely due to differences in dataset size, feature structures, feature variety, and class distributions.

Through the lens of established student persistence theories, total credit count emerged as the most important predictor in this study, strongly aligning with Tinto's (1975) emphasis on academic integration. In OHSs, where traditional social integration is minimal, academic progress is the primary persistence anchor, likely reflecting achievement, motivation, and self-regulation crucial for distance learning (Zimmerman, 2002). This resonates with recent research showing academic progression's key role in distance learning retention (Colpo et al., 2024; Hannaford, 2021; Perez et al., 2018) and highlights its greater importance when social integration is limited. Shahiri and Husain (2015) also confirmed cumulative GPA (related to credits) as a reliable success indicator.

Enrollment type, the second key predictor, supports findings by Allensworth and Easton (2007) and Nagy and Molontay (2018) and aligns with Bean and Metzner's (1985) model emphasizing background and external factors for non-traditional students. This likely proxies for unobserved variables such as prior academic preparedness (students transferring after failure face higher risks; Bedel, 2013; Jimerson & Ferguson, 2007), socioeconomic status, and initial adaptation to distance learning. Its significance highlights the impact of pre-entry conditions (Astin, 1985) and life-course factors, especially for transfers from conventional schools due to academic challenges, facing academic challenges, and higher dropout risks (Bedel, 2013; Jimerson & Ferguson, 2007).

Age, disability status, region, employment, and gender were also important predictors, confirming learner characteristics' importance in distance education (Bozkurt et al., 2015; Durak et al., 2017). Intriguingly, academic/administrative variables (credits, enrollment type, age) were more predictive than demographics (gender, employment). This might suggest that in this large-scale distance setting, individual academic momentum and entry characteristics exert a more direct influence than demographic attributes, whose impact might be mediated differently than in face-to-face settings. It challenges assumptions about universal predictors, suggesting that in this context, Tinto's academic integration and Bean and Metzner's pre-entry/background factors are particularly influential due to reduced social integration and heightened demands for individual drive.

The model struggled to predict the active/delayed class (recall = 45.8%), due to group heterogeneity and the static nature of administrative data. Static data lacks dynamic indicators (engagement, momentum, intentions) needed to distinguish slow progressors from potential dropouts. Dynamic engagement data or qualitative methods could better illuminate this group's specific challenges and motivations (cf. Bowers, 2010).

Limitations include relying solely on administrative data, omitting variables such as family background, prior achievement (e.g., middle school GPA), psychometric factors, dynamic engagement metrics (e.g., login frequency), and nuanced socioeconomic indicators. Including such data improved accuracy elsewhere (Márquez-Vera et al., 2013; Şara et al., 2015) and could better differentiate risk levels, especially for the active/delayed-graduation group. Self-reported data reliability (e.g., employment) is another limitation. Despite limitations, this study contributes to a large-scale, multi-class predictive analysis within Türkiye's open secondary education system. It empirically shows academic progress and initial enrollment conditions outweigh demographics here, refining persistence theories (Bean & Metzner, 1985; Tinto, 1975) for large-scale distance learning. The findings offer an evidence base for targeted, data-driven interventions and policies, moving beyond generic assumptions. Future research should integrate comprehensive, dynamic data, explore real-time prediction, and use clustering to better understand student subgroups.

Recommendations

Based on the findings and discussion, the following recommendations are proposed:

For Practitioners

The implementation of data-driven early warning systems (EWS) is strongly recommended to identify at-risk students using key predictors such as low credit accumulation rates, high-risk enrollment types, and specific age profiles, with these systems integrated into existing infrastructure while addressing technical needs, data integration, staff training, and ethical guidelines. Targeted interventions should be developed based on specific predictors: for students with low credit accumulation, institutions should offer proactive academic counseling, study skills workshops, and review sessions for failed courses; for high-risk enrollment types (particularly transfers due to failure), mandatory enhanced orientation programs, mentor assignments, and early support access are essential. Academic momentum should be closely monitored by tracking credit accumulation rates over time, triggering interventions when progress slows relative to enrollment duration, and implementing system alerts for below-threshold credit counts.

Institutions should enhance onboarding and communication by tailoring activities to enrollment type and identified risks, using targeted communications for important reminders and motivational feedback. Systematic investigation of barriers through periodic surveys and focus groups, especially targeting at-risk students, can help understand specific obstacles and develop strategies to address issues such as exam absenteeism. Practitioners should advocate for enriching enrollment data with crucial information such as prior academic achievement, detailed socioeconomic indicators, and distance education readiness to improve predictive accuracy. Where available, course management system integration should be explored to leverage interaction data for finer-grained analysis of student progress and risk identification.

For Researchers

Future research should integrate diverse data sources while examining heterogeneity within student groups, especially the active/delayed graduation cohort, through mixed-methods approaches. Longitudinal modeling techniques such as survival analysis would track evolving risks, while advanced machine learning and explainable artificial intelligence could improve prediction accuracy without sacrificing interpretability (Er, 2023; Goran et al., 2024). Model refinement through hyperparameter optimization and class imbalance techniques offers performance enhancement opportunities as demonstrated by recent studies (Althaqafi et al., 2025; Sahlaoui et al., 2024). Implementation of early warning systems requires rigorous evaluation of their impact on retention outcomes. Cross-context comparisons across educational systems would identify universal versus context-specific predictors, while clustering analyses could reveal distinct student subgroups. Continued exploration of diverse algorithms and validation methods remains essential for robust research comparisons.

Limitations

This study's limitations include restricted feature availability from the administrative student information system, omitting potentially influential variables such as prior academic achievement, detailed socioeconomic factors, and behavioral indicators. These omissions may constrain the models' ability to fully capture persistence factors and affect predictor interpretation. Additionally, computational constraints with our large dataset (N = 484,158) necessitated using stratified holdout validation rather than k-fold cross-validation. These limitations suggest opportunities for future research leveraging more comprehensive datasets and enhanced computational resources.

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