



**A MULTI-PARAMETER INTELLIGENT MODEL FOR EARLY PREDICTION OF
STUDENT EXPULSION RISK IN HIGHER EDUCATION INSTITUTIONS
(BASED ON THE EXPERIENCE OF THE CREDIT-MODULE SYSTEM)**

Abdurasulov Olqar Toir o'g'li

Registrar's Office, Samarkand Branch of ISFT Institute

Chief Specialist in Databases

E-mail:abdurasulovolqar123@gmail.com

Number: +998 93 999 80 49

Scientific Supervisor: Temirov Anvar Amirovich

Vice-Rector for Academic Affairs, ISFT Institute

PhD in Pedagogical Sciences, Associate Professor

E-mail:anvartemirov557@gmail.com

Number: +998 77 699 1211

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This article describes a method for identifying the risk of student dismissal early in the semester at higher education institutions. The aim of the study was to develop a simple and practical model that assesses risk using five indicators under the credit module system and to test how well it works. The model combines class absences, delays in tuition payments, midterm results, activity on the online learning platform and failure to answer calls into one 100 point scale. Students are placed into green, yellow and red zones according to their risk level. The model was tested at the Samarkand branch of the ISFT Institute in the 2025/2026 academic year with about 7,000 students and compared with the results of 2024/2025. The share of students dismissed at the end of the semester fell from 7.8% to 1.9%, and overall retention rose from 85.2% to 97.4%. The results suggest that the model can be used at other universities, although further testing is needed.



1. INTRODUCTION

In recent years, the higher education system in Uzbekistan has undergone extensive reform. The concept approved by the President's Decree No. PF-5847 dated October 8, 2019, identified improving the quality of higher education, adopting international best practices, and digitizing education as key priorities [1]. Starting from the 2020/2021 academic year, the educational process began a phased transition to the credit-module system. This procedure was introduced by Resolution No. 824 of the Cabinet of Ministers dated December 31, 2020 [2]. Under the new system, students have greater autonomy in determining their educational path, and independent study plays a significant role. At the same time, the student's responsibility for their own learning increases.

As a result of these reforms, the number of students has risen rapidly. According to data from the National Statistics Committee, at the beginning of the 2025/2026 academic year, there were 1.535 million students enrolled in higher education institutions. This figure is approximately 2.7 times higher than the 571.5 thousand students recorded in the 2020/2021 academic year (Table 1). In the current academic year, 215 higher education institutions operated in the country, 97 of which are non-state institutions. In the Samarkand region, the number of students reached 93.9 thousand [3].

1 table. Dynamics of the number of students in higher education institutions
(at the beginning of the academic year)

Academic year	Talabalar soni, ming nafar	Growth compared to the previous year, in percent
2020/2021	571,5	Foundation year
2021/2022	808,4	41,5
2022/2023	1 042,1	28,9
2023/2024	1 314,5	26,1
2024/2025	1 432,8	9,0
2025/2026	1 535,0	7,1

Source: The author calculated based on data from the National Committee for Statistics [3].

The grounds for the exclusion of a student from study are set out in the Resolution of the Cabinet of Ministers of September 13, 2025 No. 578. According to paragraph 49 of the resolution, a student who misses classes for more than 74 hours without an excuse for one semester can be expelled. Except in the case where a medical certificate in the prescribed form is provided for health reasons. A student who is studying on a contractual basis can be expelled even if he does not make the payment on time [4].

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In foreign studies, this issue has been studied for a long time. V. Tinto has shown that a student's dropout depends on how much he or she is involved in the educational process and higher education life [5, 6]. J. Bean and B. Metzner, on the other hand, have emphasized the importance of external factors such as work, family, and financial status for students who are busy and older [7]. The direction of educational data analysis uses student data to make it possible to identify students at risk in advance [8, 11]. For example, Macfadyen and Dawson proposed an early example of an early warning system based on activity data in the educational management system [9]. The Course Signals system, developed at Purdue University, is also based on giving a timely signal to the student about their results [10]. Some approaches rely mainly on mastery or platform activity. In this context, the main reasons for exclusion are clearly listed in the regulatory document, i.e., class absenteeism and payment delays [4]. Therefore, a simple model is needed that takes these factors into account along with the mastery and communication data.

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2. MATERIAL AND TECHNIQUES

2.1. Research Design and Object

The study was conducted within one institution, using a comparison of two academic years. About 7,000 students of the Samarkand branch of ISFT Institute were taken as an object. In the 2024/2025 academic year, the risk model was not applied, and work with students was carried out in the usual manner, that is, on the basis of the results at the end of the semester. In the 2025/2026 academic year, the model was introduced, and the risk score of each student was updated daily.

2.2. Analytics Metrics



The model consists of five indicators. Each of these is represented on a scale of 0 to 100, with 100 points representing the highest risk. The indicators, calculation method, and weight coefficients are given in Table 2.

Table 2. Risk Model Indicators and Weight Coefficients

Belgi ans	Bullet	How it is priced	Vazn
r ₁	Attendance	Decrease Hours Rolled to 74 Hour Milestone	0,30
r ₂	To'lov	Percentage of overdue debt on the current phase	0,25
r ₃	Intermediate control	Percentage of intermediate controls that failed	0,20
r ₄	Platform activity	Number of days without logging into the platform	0,15
r ₅	Communicate	Number of Consecutive Calls Left Without Answer	0,10

Source: Author's Development.

The attendance rate (r₁) is measured by the ratio of the hours left to the exclusion limit. As the limit, 578 hours are taken as defined in Decision No. 74 [4]. The result does not exceed 100 points.

$$r_1 = \min (100, H_q / 74 \times 100) \quad (1)$$

Here H_q is the number of hours a student leaves without excuse, and 74 is the exclusion limit.

The repayment indicator (r₂) is calculated according to the stages of contract repayment. The amount of the education contract is divided into four stages, i.e., 25, 50, 75 and 100 per cent. The indicator is equal to the ratio of the overdue debt at the current stage to the amount of that stage.

$$r_2 = \min (100, D_q / D_b \times 100) \quad (2)$$

Here D_q is the overdue loan amount, D_b is the contract amount of the current stage.

The Intermediate Control Score (r₃) indicates the percentage of intermediate controls in which a student failed to score a passing score. A maximum score of 40 percent was accepted as a passing threshold in the branch.

$$r_3 = N_q / N_j \times 100 \quad (3)$$

Here N_q is the number of intermediate controls that failed to accumulate a passing score, while N_j is the total number of intermediate controls conducted.

The Activity Score (r₄) on the platform is determined by the number of days that the student has not logged into the learning platform. If the student has not logged in for more than 7 days, the risk score will increase. For a student who has not logged in to the platform for 30 days or



more, the score will be equal to 100. In the calculation, the number of inactive days after 7 days is taken as X. If the student has been inactive for more than 7 days, X is zero.

$$r_4 = \min (100, X / 23 \times 100) \quad (4)$$

The Communication Indicator (r_5) takes into account situations in which the student or his/her responsible representative does not respond to calls from the conductor or operator. If there is no response three times in a row, the score reaches 100.

$$r_5 = \min (100, K_j \times 33,3) \quad (5)$$

Here K_j is the number of consecutive unanswered calls.

2.3. Risk index and weight ratios

A student's overall risk index (R) is found as a weighted sum of five indicators.

$$R = 0,30 \times r_1 + 0,25 \times r_2 + 0,20 \times r_3 + 0,15 \times r_4 + 0,10 \times r_5 \quad (6)$$

The sum of the weight coefficients is 1.00, so R is also rated on a scale of 0 to 100. The greatest weight is given to attendance and pay, since it is these two factors that are indicated in the regulatory document as the direct basis for exclusion [4]. Intermediate control, platform activity, and communication received smaller weight as additional markers of risk.

2.4. Risk Areas and Management Measures

Based on the risk index, students are divided into three zones. A specific measure is defined for each zone (Table 3). The zone is determined only by the R score.

Table 3. Risk Zones and Appropriate Measures

Area	R balli	status	Measure to be applied
Green	0 to 30 (30 not included)	steady state	No intervention required
Yellow	30 to 60 (60 not included)	Preventive e'tibor	The assignment to the tutor is automatically generated and the contact center will issue a note to the student
Red	60 dan 100 gacha	Critical risk	The matter will be urgently directed to the dean's office

Source: Author's Development.

To explain the calculation, let's use a conditional example. Let's take a student who has left 52 hours of class in one semester, owed half of the current stage amount, failed to pass one of the four intermediate controls, has not logged into the platform for 15 days, and has not responded to a single call from the tutor. His indicators will be as follows: $r_1 = 70,3$, $r_2 = 50,0$, $r_3 = 25,0$, $r_4 = 34,8$ va $r_5 = 33,3$. Xavf indeksi $R = 0,30 \times 70,3 + 0,25 \times 50,0 + 0,20 \times 25,0 + 0,15 \times 34,8 + 0,10 \times 33,3 = 47,1$ score. That means that student falls into the yellow zone and is assigned to work with the tutor.



The important point is that the model does not automatically exclude the student. It only signals the responsible staff at the time of providing assistance. The decision to expel is made by the individual on the basis of the normative document.

2.5. Effectiveness assessment

Effectiveness was evaluated on six indicators: the percentage of students who reached the 74-hour limit, the percentage of those who owe intermediate controls, the percentage of students whose payment schedule was closed on time, the percentage of students who were not expelled in the yellow zone, the percentage of those who were expelled at the end of the semester, and the overall retention rate. The retention indicator refers to how many students at the beginning of the school year were absent for all reasons.

The difference in shares in the two academic years was verified with a z criterion for the two shares. In the calculation, the number of students in both years was assumed to be 7,000, with a significance level of 0.05. The difference was also calculated as a 95 percent confidence interval.

3. RESULTS

The model was applied to approximately 7,000 students of the branch in the 2025/2026 academic year. The results are compared with the indicators for the 2024/2025 academic year in 4 tables.

Table 4. Comparative Effectiveness of the Early Warning Model

bullet	2024/2025 (model not applied)	2025/2026 (model applied)	Change
Reached 74 hours of instruction	8,6% (602 nafar)	2,1% (147 nafar)	4,1 decreased by a factor
Those owed from intermediate control	19,4%	5,3%	3,7 decreased by a factor
Timely payment schedule closures	68,5%	91,4%	22,9 increased by percentage points
Missed in yellow zone	31,2%	84,7%	53,5 increased by percentage points
Withdrawn at the end of the semester	7,8% (546 nafar)	1,9% (133 nafar)	4,1 decreased by a factor
Global Retention	85,2%	97,4%	12,2 increased by percentage points

Source: Attributed by the author based on the data of the Samarkand branch of ISFT Institute.



The most significant change was observed over the course of time. The proportion of students who reached the 74-hour threshold decreased from 8.6 percent (602) to 2.1 percent (147 students), i.e., 4.1 times. The difference was statistically significant ($z = 17.1$, $p < 0.001$), with the 95 percent confidence interval of the difference ranging from 5.8 to 7.2 percentage points. The proportion of students who owe intermediate control decreased from 19.4 percent to 5.3 percent, which is 3.7 times less.

Fee discipline has also improved. The proportion of students who closed the payment schedule on time increased from 68.5 percent to 91.4 percent, an increase of 22.9 percentage points. 84.7 percent of students who fell into the yellow zone continued their studies without being expelled. In the 2024/2025 academic year, this figure was 31.2 percent. This means that the difference was 53.5 percentage points. At the end of the semester, the share of students who were expelled decreased from 7.8 percent (546) to 1.9 percent (133 students). This also means 4.1 times less. The difference was statistically significant ($z = 16.2$, $p < 0.001$), with the confidence interval ranging from 5.2 to 6.6 percentage points. The overall retention rate increased from 85.2 percent to 97.4 percent. This represents an increase of 12.2 percentage points, or about 14.3 percent in relative terms. Simply put, in the 2024/2025 academic year, about 100 out of every 15 students dropped out, while in the 2025/2026 academic year, this number was close to 3.

4. DISCUSSION

The results obtained showed that it was beneficial to monitor the risk throughout the semester rather than at the end of the semester. The proportion of students who were expelled decreased by 4.1 percentage points, while the retention rate increased by 12.2 percentage points. This result can be explained as follows. First, the model aggregated the scattered data into a single point, and the staff in charge began to anticipate the risk. Second, the fact that a specific measure and responsible party were identified for each zone accelerated the intervention. This situation is consistent with Tinto's idea: early contact with the student helps him or her to become a part of the learning process [5, 6]. The results are also similar to the experience of overseas early warning systems. In these, too, the main idea is to signal to the student or teacher before the problem gets bigger [9, 10]. The difference is that the proposed model is directly tied to the exclusion frameworks in the regulatory document. For this reason, great weight has been given to attendance and payment. At this time, the results need to be interpreted carefully. First, the study was conducted in a single institution. Second, there was no management group and only two academic years were compared, so not all of the change can be attributed to the model. For example, decision 578 was made in September 2025, and this model coincided with the beginning of the school year in which the model was introduced [4]. Such external factors may also have influenced the outcome. Thirdly, the weight coefficients were not checked statistically, they were determined by the significance in the regulatory document. Fourth, the model does not explain the cause of the risk, it only determines it through a conversation between the tutor



or the dean. Fifth, it is necessary to ensure the confidentiality of the student's personal data when it is handled. In further studies, it would be advisable to determine weights using methods such as logistic regression based on data from previous years, to measure the proportion of false positives, and to test the model in other branches and higher education institutions.

5. CONCLUSION AND PRACTICAL RECOMMENDATIONS

The study showed that in the credit module system, students' proficiency and discipline can and should be monitored on a multi-parameter model throughout the semester rather than at the end of the semester. A 100-point risk index based on five indicators divided students into green, yellow, and red zones, allowing for a specific measure to be set for each zone. In the academic year in which the model was applied, the share of students who were expelled decreased from 7.8 percent to 1.9 percent, while the overall retention rate increased from 85.2 percent to 97.4 percent. Percentage of students who fell into the yellow zone 84,7 percent continued to study.

The following recommendations are given for other institutions of higher education:

1. Pooling data from a single database: attendance, payment, remote control, platform activity and communication.
2. Update the risk score regularly, daily if possible.
3. Determine in advance the department responsible for each zone and the duration of work.
4. Check and clarify weight ratios annually based on new data.
5. Use the model only as a tool to help, and ensure that the decision to exclude is made by a person based on regulations and protect personal data.

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