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Research Article

The Dynamics of School Dropout in The Turkish Higher Education System

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Abstract

Introduction: Student dropout is not only an individual failure but also leads to the ineffective use of public resources, the worsening of educational inequalities, and disruption in the labor market, thereby preventing long-term development. The aim of this study is to address the methodological gap in the area by utilising a large-scale dataset of approximately 2.9 million students covering the 2016–2024 period.

Method: The Fine-Gray Competing Risks Model, extended with time-varying coefficients, was employed, which considered graduation not simply as a censoring process, but as a competing risk with dropping out. Based on the higher education students database, the impacts of gender, age, disability status, parental education level, distance of residence, and entrance exam score type on the risk of dropout were explored.

Results or Findings: Students accepted based on quantitative test scores had the lowest dropout risk. Students whose parents were college graduates initially faced a relatively higher risk of dropping out in specific fields; this risk increased dynamically in quantitative and verbal fields; Distance represented a constant marginal risk. The probability of dropping out also increases with age; male students initially had a lower risk, but this difference increased over time.

Discussion or Conclusion: These findings may suggest that student dropout rates at Turkish universities may generally result from relatively stronger social factors. The continued education of students with disabilities in areas outside the quantitative fields and the growing advantage in school retention rates among male students presents a challenge to traditional views on the vulnerability of higher education.

Keywords: university dropout, competing risks, administrative data, disability, parental education

JEL Codes: I23, I24, C41

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Öz

Giriş: Öğrencilerin okulu bırakması yalnızca bireysel bir başarısızlık olmakla kalmayıp, kamu kaynaklarının verimsiz kullanılmasına, eğitim eşitsizliklerinin derinleşmesine ve işgücü piyasasında aksamalara yol açarak uzun vadeli kalkınmayı engellemektedir. Bu araştırma, 2016–2024 periyodunu içeren yaklaşık 2,9 milyon öğrenciyi kapsayan geniş çaplı bir veri seti kullanarak alandaki metodolojik boşluğu doldurmayı ve bir bakış açısı sunmayı amaçlamaktadır.

Yöntem: Çalışmada, mezuniyeti sadece bir sansürleme süreci olarak değil, aynı zamanda okul terkiyle rekabet eden bir risk olarak ele alan zamanla değişen katsayılarla genişletilmiş Fine-Gray Rekabet Eden Riskler Modeli kullanılmıştır. Üniversite öğrencileri veritabanına dayalı olarak, cinsiyet, yaş, engellilik durumu, ebeveynlerin eğitim düzeyi, ikamet yerinin uzaklığı ve giriş sınavı puan türünün okul terk riski üzerindeki etkileri incelenmiştir.

Sonuçlar ya da Bulgular: Sayısal test puanlarına göre kabul edilen öğrencilerin okuldan ayrılma riski en düşükken, ebeveynleri üniversite mezunu olan öğrenciler belirli alanlarda başlangıçta göreceli olarak daha yüksek bir okul terk riskiyle karşı karşıya kalmaktadır. Bu risk, sayısal ve sözel alanlarda dinamik bir şekilde artmaktadır. Mesafe, sabit bir marjinal riske sahip olmakta, okul terk etme olasılığı da yaşla birlikte artmaktadır. Erkek öğrencilerin başlangıçta riski daha düşükken, bu fark zamanla artış göstermektedir.

Tartışma ya da Yapılan Çıkarımlar: Bu bulgular, Türk üniversitelerindeki üniversite terk etme oranlarının genel olarak nispeten daha güçlü sosyal faktörlerle bağlantılı olabileceğini gösterebilir. Engelli öğrencilerin sayısal alanlar dışında eğitimlerine devam etmeleri ve erkek öğrenciler arasında okulda kalma oranlarının artması, yükseköğretimin kırılabilirliğine dair geleneksel görüşleri yeniden değerlendirmeye açmaktadır.

Anahtar Kelimeler: üniversite terki, rekabet eden riskler, idari veriler, engellilik, ebeveyn eğitimi

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Introduction

Human capital accumulation is vital for socio-economic sustainability and has contributed to the expansion of higher education across the globe in recent years (Aina, 2013). The greater inclusion of diverse segments of population in university education has been seen as a sign of the success of education policies. This mass participation process in higher education institutions has, alongside other parallel problems, yielded a noticeable increase in the difference between the number of students enrolling in schools and the number of students graduating, in other words, it has increased the significance of the phenomenon of university dropouts.

University dropout reflects not only a personal failure but also the use of public resources inefficiently, further contributing to educational inequality and labor market disruptions (Behr et al., 2020; Huynh-Cam et al., 2025; Giraldo et al., 2025). This represents a waste of institutional and public resources and stands in the way of long-term development (Jaksztat et al., 2021).

Recent work confirms that dropping out of the university is not just an issue of personal factors but can be caused by a complex combination of academic, economic, and mental factors (Quimiz-Moreira et al., 2025; Valencia-Arias et al., 2025). Throughout the post-pandemic period, in specific, academic stress and mental distress have arisen as significant drivers of students' decisions to leave school (Gonzalez et al., 2025). Using target-oriented surveys on student engagement and performance to determine these risk indicators early on has been crucial for those institutions aiming to apply timely student engagement strategies before students make the final choice to leave school (Lizarte Simon & Gijon Puerta, 2022).

Research into the reasons why students drop out of school has historically focused on students' interactions with their schools and their individual background characteristics, indicating that school dropout essentially stems from weaknesses and failures in social adjustment processes (Tinto, 1975; Bean, 1980). Applied research has also shown that social and economic conditions are key determinants of school dropout, with parental education level and family income having a significant impact on students' motivation to continue to university (Vignoles & Powdthavee, 2009; Aina, 2013). These studies report that students with insufficient intellectual capital and financial support are more vulnerable to being pushed out of the system, even if they have high academic potential. It has been reported that difficult economic conditions within the family, in combination with academic dissatisfaction, are the key factors driving early withdrawal from higher education (Nurmalitasari et al., 2023). Economically disadvantaged students are found to be at a much higher risk of school dropout in comparison to their less disadvantaged fellow students, a disadvantage that is observed even when their previous academic performance is taken into consideration. Continued financial difficulties during the education process, the need to work, and economic pressures such as family responsibility play a key role in students' decisions to drop out by causing them to neglect their academic duties (Apumayta et al., 2024).

Sociocultural and economic status, as well as individual and economic factors, are key factors in the risk of dropping out of university, with physically disadvantaged individuals found to be at higher risk than students without disabilities (Russmann et al., 2024). Geographic factors, which can be considered hidden costs, and opportunities for campus access are also among the risk factors for university dropout. Opening new university campuses is said to lower the risk of university dropout by reducing the time and financial costs of accessing universities (Oppedisano, 2011).

Earlier studies on school dropout have tended to rely on cross-sectional survey data with limited samples and view school dropout as a simple binary outcome (Araque et al., 2009; Pedditzi, 2024; Venkatesan et al., 2024). Standard survival-analysis methods, such as Cox regression, treat graduates as censored data, resulting in an overestimation of dropout risks.

This study aims to fill the mentioned methodological gap and provide a universe-level overview of the literature by utilizing a large-scale administrative dataset obtained from the Turkish Statistical Institute (TurkStat) higher education students database, covering approximately 2.9 million students, instead of survey data, thereby overcoming the sample limitation in the literature (TurkStat, 2026). The Fine-Gray Competing Risks Model, extended with time-varying coefficients, was used as the analysis method, modeling graduation not as a censoring event but as a risk competing with dropout. This approach allowed estimating the effects of variables such as gender, age, disability status, parental education, and entrance exam score type on the pure dropout risk, adjusted for graduation probability. Student risk of dropping out of university was estimated in two ways: overall and by type of entrance exam score.

Literature

The decision to drop out of higher education, and more generally, to leave the education system, is a multidimensional issue resulting from a set of factors, from individual demographic factors to family situation, educational background, and other institutional conditions. School leaving choices are commonly addressed within the concepts of lack of socio-academic adaptability (Tinto, 1975) and cost-benefit evaluation of human capital investments (Becker, 1962); however, conventional approaches tend to view these dropouts as one-dimensional outcomes of failure (Kehm et al., 2019; Behr et al., 2020). To adequately evaluate hypotheses concerning variables such as age, gender, and parents' educational level, it is necessary to model graduation and school dropout not as two independent events, but as strategically competing, alternative risks. Student decisions to remain in school or drop out reflect a choice being made between the expected utility of a degree and the expected utility of alternative pathways outside the higher education system. The key point is that the expected utility of these two alternative pathways is not likely to be constant over the duration of the student's registration. Tinto's integration difficulties are most common in the early periods of academic life, when social and educational challenges are most apparent; nevertheless, Becker's cost-benefit analysis suggests that these problems may become more significant as students approach degree completion, as lost opportunities, family conditions, and external opportunities become more evident.

The traditional expectation in contexts such as Türkiye that men should join the labor force and contribute to their families' livelihoods, together with legal systems such as the postponement of mandatory military service for male students who are in active enrollment, may function as a systemic incentive that not only helps men remain in the education system initially, but also cumulatively widens the retention gap in their favor over time (Mouganie, 2020). It is widely viewed that higher age generally results in an increased risk of dropping out of school owing to higher alternative opportunity costs and social adaptation challenges related to generational differences among students (Portela et al., 2021; Bellare et al., 2023; Sallai et al., 2023); however, this relationship may not be the case in all academic fields; in specific disciplines such as language studies, the intrinsic motivation and integration capabilities of adult learners can progressively mitigate and eventually eliminate the initial disadvantages of older age as the educational process continues (Kasworm, 2010). Personal factors such as physical or intellectual disabilities are typically identified as factors that introduce additional barriers and lead to a higher risk of dropping out of school (Russmann et al., 2024; Giraldo et

al., 2025); however, this can be different in highly centralized and competitive university entrance systems. Students with disabilities who overcome the highly competitive selection procedures to enter higher education may represent a particular subgroup with greater than average academic strength and motivation, and institutional programs of higher education may be better able to provide them with the support they need to remain in their higher education programs. The beneficial value of this sorting effect likely relies on the field of study: in programs with a quantitative focus, where structural barriers such as mandatory physical activity and limited physical access may eliminate the resilience advantage of this subgroup; whereas in verbal or language-based programs, these structural barriers are less apparent, and the protective effects of both institutional support and the selective process can be observed more distinctly. Academic burnout has continued to be a theoretically viable mediating process that could lead to an increased willingness to leave one's job, in particular in high-pressure workplaces (Candelo-Meneses et al., 2026); since administrative datasets are rarely able to directly reflect psychological indicators, this mechanism should be taken as an unobservable pathway that informs future data collection efforts, and not as a concept directly measured in the present research.

Parents' educational backgrounds and socioeconomic status are important background influences on academic continuity. Studies conducted in Italy, Spain, and the United States consistently indicate that low parental educational level and financial constraints significantly contribute to the risk of dropping out of school (Aina, 2013; Araque et al., 2009; Pusztai et al., 2025; Curbani et al., 2026; di Biase & Giusino, 2026). The influence of family background, however, must be viewed in its specific context. Against general expectations, students from well-educated and wealthy families may actually be at higher risk of facing a situation that could be described as luxury dropout (Johnes & McNabb, 2004; Belloc et al., 2011). Highly educated and wealthy parents' children have a degree of economic security that gives them the opportunity to voluntarily drop out of a program that does not meet their expectations and look for alternative possibilities. This socioeconomic safety net has produced a growing and increasing trend of strategic school dropouts over time; as opposed to their vulnerable peers, these students are increasingly leaving the education system as they continuously consider better career and educational opportunities available outside of school (Tinto, 1988; Belloc et al., 2011). Sociologically disadvantaged students, on the other hand, usually see higher education as the main mechanism for social advancement, leading to a situation of compulsory persistence in which they feel obligated to complete their programs regardless of their level of happiness.

Looking at it from the institutional and environmental points of view, the physical distance between a student's place of origin and the university town is a key factor affecting retention during the academic process (Zeragaber et al., 2024; Huynh-Cam et al., 2025). Garza and Fullerton (2018) note that this distance creates a dilemma: it can help students integrate into campus life, while also increasing financial and mental stress; however, geographic distance alone does not affect retention. Students' school leaving decisions are significantly influenced by institutional heterogeneity, which represents unobservable factors such as quality differences among universities, regional inequalities, and variations in institutional support mechanisms across Turkish institutions. Differences in the quality of institutional opportunities offered by universities in different geographic locations thus make the impact of distance more complex. Unlike academic and social integration experiences that evolve progressively over time, geographic distance and the related economic burden serve as a more stable, structural limitation throughout a student's educational experience (Aina et al., 2022).

The type of entrance exam score that shows how academic a student is one of the main drivers of the risk of early school leaving. The studies show that students in quantitative fields generally have lower dropout rates than those in the social sciences (Araque et al., 2009; Opazo et al., 2021). This distinction in Türkiye's higher education system is expressed more correctly by four different entry categories rather than a simple quantitative-verbal distinction: quantitative, equal weighted, verbal, and language score types; each represents a different structural candidates pool with its own specific selection mechanisms. This is often attributed to the difficult nature of mathematics and physics subjects, but it is necessary to account for their strong self-selection characteristics. School dropout risks differ across score types and do not simply reflect curriculum challenges. Students who choose and succeed in math programs may, in fact, differ fundamentally from their classmates in the verbal fields in terms of unobservable academic capacity, personal motivation, and labor market preferences, which suggests that this selection effect directly supports higher academic continuity among these students. The language skills category deserves special focus in this context, as it generally involves a much smaller and more expert pool of applicants than the other three categories; consequently, its estimates may be less precise and more vulnerable to the characteristics specific to a given program or group of students.

The summarized theoretical and empirical studies indicate that the factors related to university dropout may vary according to individual, socioeconomic, and institutional characteristics. Based on this framework, the present study tests the following hypotheses: H1: There is a significant difference in the risk of university dropout between male and female students. H2: The risk of dropping out increases as the age of university enrollment increases. H3: Parental education level has a significant effect on students' risk of dropping out. H4: The effect of disability status on the risk of dropping out differ according to the type of score students were selected based on. H5: An increase in the distance between the student's place of residence and the university increases the risk of dropping out. These hypotheses are tested separately for different score types within the framework of the Fine-Gray model, which treats graduation as a competing risk.

Data

Although the scope, types, and number of exams have changed over time, this study covers scores that are primarily weighted toward quantitative skills, verbal skills, equal weighted of quantitative and verbal skills, or foreign language skills. In addition to these, it is also possible to enter universities through assessments of art skills and basic skills in all fields. Apart from skills tests, exams and scoring systems for entrance to undergraduate programs have changed names over time but are primarily grouped into quantitative (QUANT), verbal (VERB), equal weighted (EW), and language (LANG) categories.

The dataset was compiled to cover the years 2016–2024 and was obtained on February 11, 2026, from the Department of Social Statistics at the Turkish Statistical Institute (TurkStat) under a scientific research participation authorization. Data from TurkStat (2026) higher education students database was filtered to eliminate missing records and to include only registered, voluntarily dropped out, and graduates aged 24 and under, thus excluding second university registrations. In this study, the concept of dropping out was limited to voluntary withdrawal from the higher education system; those who transferred between institutions or programs, who temporarily paused their studies, or who were suspended involuntarily due to academic failure, disciplinary measures, etc., were not categorized as dropouts. This narrow definition allows the model to distinguish in a unique way between the model's dynamics of strategic dropouts, which are initiated by students themselves, and involuntary exclusions from

the system. This methodological decision, distinguishing voluntary dropouts from dismissals for academic reasons, basically prevents the mixing of two fundamentally different sociological dynamics. Compulsory dropouts are generally attributed to academic problems and socioeconomic challenges in the literature, whereas voluntary dropouts mainly reflect a rational decision and an assessment of alternative costs (Tinto, 1975; Kehm et al., 2019; Jaksztat et al., 2021), although the present dataset does not include direct survey measures of student motivation or intent that would allow this interpretation to be tested. The exclusion of involuntary withdrawals may allow this study to better capture the effect of strategic decisions and, in this way, enable the possibility of observing phenomena such as luxury dropout, where students from highly educated parents may choose to leave programs that fail to meet their expectations in favor of more beneficial external opportunities. The raw dataset obtained from TurkStat (2026) originally consisted of approximately 10,740,000 student registrations. The final dataset of 2864506 records shown in Table 1 was obtained following a series of filtering steps. The data set used was an unprocessed statistical data set; records with missing cell information were therefore omitted from the analysis. Records from 2016 and later were included in the analysis to ensure the use of more accurate information. The analysis also excluded records in the raw data set that did not concern undergraduate education. Ultimately, only those who voluntarily left school were considered to fall under the definition of university dropouts. The majority of these exclusions reflect structural filtering criteria rather than random data loss; therefore, the estimated relationships are not systematically biased by them. The possibility that unobserved factors jointly affect data quality and the risk of dropping out cannot be entirely ruled out, however, as is the case with any larger administrative records. The time these students spent in university education (DURATION) was taken as the education semester. Due to possible outdated records, the DURATION variable was included in the study for records with a maximum of 20 semesters.

To explain the voluntary withdrawal of students from university, the following variables have been utilized:

- students' gender (GENDER=0 for women and GENDER=1 for men, where women serve as the reference category),
- students' age at enrollment (AGE),
- students' disability status (DISABILITY=0 if not disabled, DISABILITY=1 if disabled, with non-disabled students acting as the reference group),
- students' parental education level, categorized into three groups as low, medium, high (PARENTAL)
- the straight-line distance between the student's residence on the date of registration and the department they enrolled in (DISTANCE); and
- the type of score used for the student's placement in the university department (ENTRY_SCORE_TYPE) which is utilized to stratify the analysis into four distinct sub-models, and the university where the student is registered to control for unobserved heterogeneity at the institutional level.

Preliminary information regarding the variables used in the study is presented in Table 1.

Table 1*Descriptive Statistics*

Variable	Category	Total	Current Students	Dropouts	Graduates
STATUS	Total	2864506	21.49	4.53	73.98
	LANG	3.64	0.87	0.22	2.55
ENTRY_SCORE_	EW	34.34	7.91	1.67	24.75
TYPE (%)	QUANT	42.94	8.66	1.44	32.84
	VERB	19.08	4.05	1.20	13.83
DISABILITY (%)	Without disabilities	99.35	21.35	4.50	73.49
	With disabilities	0.65	0.14	0.03	0.48
GENDER (%)	Women	44.23	10.55	2.71	30.97
	Men	55.77	10.94	1.83	43.00
PARENTAL (%)	Low education	3.54	0.69	0.20	2.66
	Medium education	20.53	4.17	1.04	15.32
	High education	75.93	16.63	3.30	56.00
DISTANCE (Mean)	-	244.64	301.49	377.30	220.00
DURATION (Mean)	-	5.70	2.88	3.36	6.66
AGE (Mean)	-	19.12	19.18	19.30	19.10

Note. The dataset belonging to the TurkStat and calculated by the author using R statistical software.

As detailed in Table 1, the dataset contains 2864506 records: 73.98% graduates, 21.49% current students, and 4.53% dropouts. The population is composed mainly of males and non-disabled individuals, the most frequently entered type is quantitative scores and the vast majority of students have parents with a high level of education. On average, students enroll at the age of 19. Dropouts have the shorter mean duration of education and the greater geographical distance to their universities compared to graduated students.

Methodology

This study employs the competitive risks survival analysis methodology, extended with time-varying coefficients. Graduation in higher education provides a competitive risk against the target event of school dropout (Fine & Gray, 1999). Viewing graduates simply as censored data implies that they are at continued risk of dropping out, which results in an overestimation of dropout probabilities and biased outcomes (Fine & Gray, 1999; Geskus, 2024).

Cumulative Incidence Function (CIF) is used to calculate the probability of an event of type k occurring by a specific time t , taking into account the presence of other competing risks (Kalbfleisch & Prentice, 2002). CIF is mathematically expressed as follows for cause k .

$$F_k(t; Z) = P(T \leq t, \epsilon = k | Z) = \int_0^t \lambda_k(u; Z) S(u; Z) du \quad (1)$$

Here, T represents the time of failure, ϵ represents the event type (e.g., 1=Dropout, 2=Graduation), Z represents the covariate vector, $\lambda_k(u; Z)$ represents the hazard function for the k th event, and $S(u; Z)$ represents the probability of survival without any event occurring (Sestelo et al., 2024). Using this notation, the total probability of events at any given time can be decomposed into the sum of the probabilities of the event of interest and competing events.

Fine and Gray (1999) developed the proportional hazards model, which allows for the direct modeling of the CIF for competing risks. The subdistribution function for the event of interest is defined as follows.

$$\lambda_1^*(t; Z) = \lim_{\Delta t \rightarrow 0} \frac{1}{\Delta t} P\{t \leq T \leq t + \Delta t, \epsilon = 1 | T \geq t \cup (T \leq t \cap \epsilon \neq 1), Z\} \quad (2)$$

Standard survival analysis removes individuals from the risk set when a competing event (graduation) occurs, whereas in the Fine-Gray approach, individuals who experience a competing event are kept in the risk set as if they had an infinite failure time for the event of interest. This situation implies that those who experience the competing risk event have a zero probability of experiencing the event of interest but are represented in the analysis set by being weighted.

The model uses the following proportional hazards structure to estimate the effect of covariates:

$$\lambda_1^*(t; Z) = \lambda_{10}^*(t) \exp(Z^T \beta) \quad (3)$$

The basic subdistribution risk function $\lambda_{10}^*(t)$ and the coefficient vector β showing the effect of covariates on cumulative incidence are shown here. Parameter estimation of the model is carried out by maximizing the partial likelihood function. In the Fine-Gray model, the risk set at time t consists of individuals who have not yet experienced any event and individuals who have previously experienced the competing event.

When the censoring mechanism is random but the competing risk is informative, Fine and Gray used the inverse probability of censoring weighting technique for individuals in the risk set. The weight used for the i th individual in the prediction equation is specified below:

$$w_i(t) = \frac{\hat{G}(t)}{\hat{G}(X_i \Delta t)} \quad (4)$$

The censoring distribution $\hat{G}(t)$ is the Kaplan-Meier estimate, and $X_i = \min(T_i, C_i)$ is the observed duration. The weight is 1 if the individual has not experienced an event at time t and is uncensored, i.e., still at risk. If the individual has experienced the competing event, they continue to be held in the risk set with a weight that decreases over time, depending on the probability of still being under observation at time t .

The coefficients obtained from the Fine-Gray model are interpreted as the subdistribution hazard ratio (SHR). If $\text{SHR} > 1$ for a variable, an increase in that variable raises the cumulative dropout probability; if $\text{SHR} < 1$, it lowers the probability.

One of the key assumptions of the standard Fine-Gray model is the Proportional Sub-Distribution Hazards (PSH) assumption, which states that the hazard ratios of the joint variables remain constant over time. The Schoenfeld residuals method is utilized (Schoenfeld, 1982).

This method evaluates whether the scaled Schoenfeld residuals for each covariate are independent of time; a statistically significant correlation between these residuals and time indicates a violation of the proportional hazards assumption. When the PSH assumption is violated, that is, when it is found that the impact of the variable is constantly changing, the model must be extended by adding time-varying coefficients to avoid parametric deviations. This is implemented by adding an interaction term between the covariates and a time function $f(t)$, and the standard proportional hazard structure is changed as follows:

$$\lambda_1^*(t; Z) = \lambda_{10}^*(t) \exp(Z^T \beta + Z^T \gamma f(t)) \quad (5)$$

Here, γ denotes the coefficient vector for the time interaction. To specify the most suitable functional form for the time component, different forms, such as linear, logarithmic, and square-root, are considered based on the Akaike Information Criterion (AIC). Given that a linear time function $f(t) = t$ provides the best fit and results in the least loss of information, the dynamic SHR for any time period t can be computed algebraically as $SHR(t) = \exp(\beta + \gamma t)$. In this study, to reveal the dynamic and cumulative effects of time-dependent covariates during the training process, these specific hazard ratios were estimated and presented cross-sectionally for the 1st, 4th, 8th, and 12th periods.

Findings

Using the Fine-Gray competing risks model, this study analysed students' risk of dropping out of universities they entered with various types of scores and their graduation status. The Proportional Subdistribution Hazards (PSH) assumption, used to test the hypothesis that parameters of the model are constant over time prior to implementing the Fine-Gray competing risks survival analysis model, was analyzed using the Schoenfeld residuals method. The PSH test results for each model are summarized in Table 2 for the global coefficient.

Table 2

Schoenfeld Residuals Test Results for Proportional Subdistribution Hazards Assumption

Model	Test Statistics	p-Value
Quantitative	151.68	0.00
Equal Weighted	291.46	0.00
Verbal	198.99	0.00
Language	36.11	0.00

Note. The dataset belonging to the TurkStat and calculated by the author using R statistical software.

The summary of the global Schoenfeld test findings in Table 2 suggests that the models are statistically significant, and individual tests also show that all independent variables included in the four models are significant, with the exception of disability status. This result shows that the hazard ratios for the associated variables do not remain constant over time and that the proportional hazards assumption, a critical assumption of the standard Fine-Gray model, is broken. In order to correct for the parametric biases arising from this assumption violations and to model the dynamic effects, time-varying coefficients were integrated into the

model. The disability status was excluded from the time-interaction since it does not violate the proportional hazards assumption.

To determine most proper time function to use in the modeling of time-varying coefficients, different functional forms were checked, then the values obtained for the AIC are listed in Table 3 for purposes of comparison.

Table 3

Model Selection for Functional Forms of Time Components based on AIC

Model	Linear	Log	Square Root
Quantitative	744114	744138	744133
Equal Weighted	840513	840595	840588
Verbal	568315	568375	568373
Language	86833	86837	86838

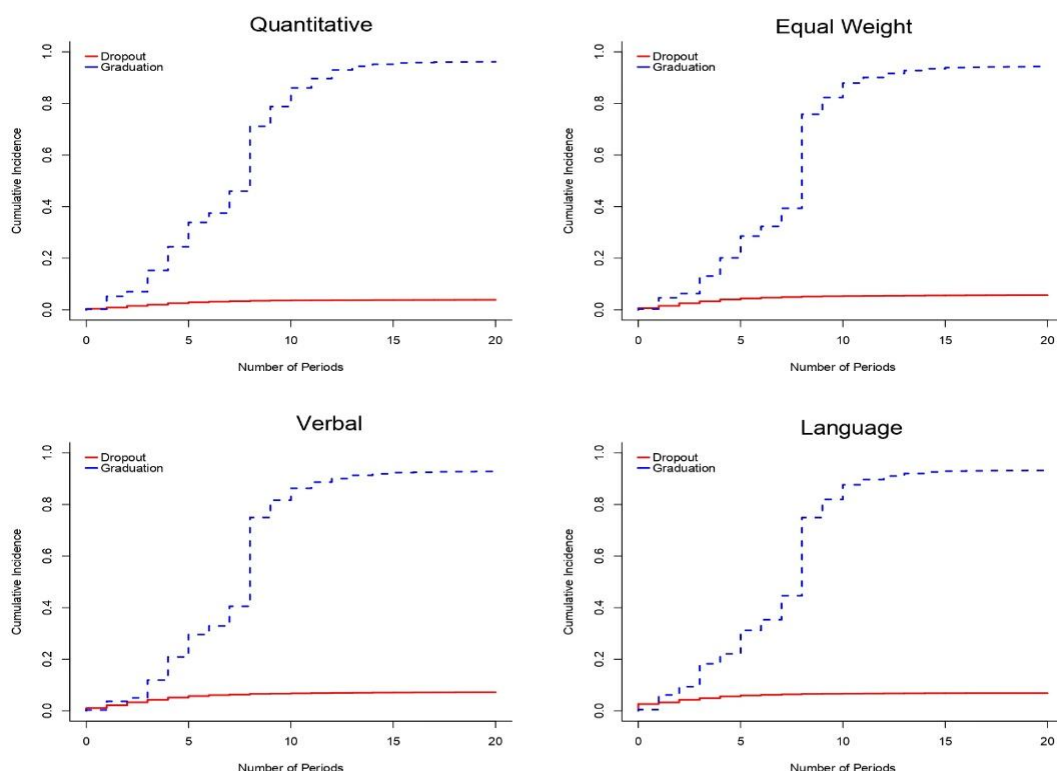
Note. The dataset belonging to the TurkStat and calculated by the author using R statistical software.

Table 3 reveals that the AIC values indicate the linear time form results in the least information loss across all sub-type models; and therefore, in estimating time-varying coefficients, the linear time component was considered as the interaction term. To control for unobserved heterogeneity at the institutional level, the university interaction effect was included in the model.

The time course of the risks to which students are subject throughout their educational lifetime was illustrated graphically using the cumulative incidence function. The CIF graphs developed for the four models are presented together in Figure 1.

Figure 1

Cumulative Incidence Function Estimates for Dropout and Graduation Probabilities



Note. This figure was created via R statistical software where Arial font customization is not supported.

Analysis of the cumulative probabilities of dropout and graduation events encountered by students throughout their educational processes showed that graduation events exhibited a dominant character. The CIF graphs in Figure 1 shows that the probability of graduation rises rapidly as the number of periods increases, approaching 0.90 levels, while the probability of dropout remains at a very low level. This finding indicates that the vast majority of students in the sample complete the system with graduation, but a certain segment cumulatively increases their risk of dropping out over time. The general trend is pretty consistent across all fields, but there are small differences in risk levels based on the specific academic field.

The final Fine-Gray model estimation outputs, after adjusting for assumption violations, clustering effects at the university level and extending with a linear time function, are described in Table 4 in terms of SHR. To allow for a detailed review of the basic model parameters, the raw basic coefficients, standard errors, and p-values for both the main effects and the time-interaction terms are given in Appendix 1. The model estimates are expressed in a way that illustrates the dynamic effects of time-varying coefficients as of the beginning of the study, the 4th period, the 8th period and the 12th period.

Table 4*Fine-Gray Model Prediction Results with Time-Varying Coefficients*

Model	Coefficient	Period 1	Period 4	Period 8	Period 12
Quantitative	GENDER	0.602***	0.536***	0.460***	0.394***
		(0.586, 0.619)	(0.525, 0.548)	(0.443, 0.476)	(0.371, 0.418)
	AGE	1.089***	1.106***	1.129***	1.152***
		(1.076, 1.102)	(1.096, 1.116)	(1.112, 1.145)	(1.125, 1.180)
	PARENTAL-Medium	1.133***	1.142***	1.154***	1.166**
		(1.049, 1.223)	(1.078, 1.209)	(1.054, 1.263)	(1.003, 1.355)
	PARENTAL-High	1.054	1.067**	1.084*	1.102
		(0.980, 1.135)	(1.010, 1.127)	(0.995, 1.182)	(0.954, 1.272)
	DISTANCE	1.001***	1.001***	1.001***	1.001***
		(1.001, 1.001)	(1.001, 1.001)	(1.001, 1.001)	(1.001, 1.001)
	DISABILITY	1.327**	1.327**	1.327**	1.327**
		(1.007, 1.747)	(1.007, 1.747)	(1.007, 1.747)	(1.007, 1.747)
Equal Weighted	GENDER	0.590***	0.520***	0.440***	0.371***
		(0.577, 0.604)	(0.510, 0.530)	(0.425, 0.455)	(0.351, 0.393)
	AGE	1.056***	1.090***	1.138***	1.187***
		(1.047, 1.066)	(1.082, 1.098)	(1.123, 1.152)	(1.163, 1.211)
	PARENTAL-Medium	1.041	1.001	0.950	0.901
		(0.978, 1.109)	(0.953, 1.052)	(0.880, 1.025)	(0.796, 1.020)
	PARENTAL-High	1.004	0.983	0.956	0.930
		(0.945, 1.067)	(0.938, 1.031)	(0.889, 1.028)	(0.826, 1.046)
	DISTANCE	1.001***	1.001***	1.001***	1.001***
		(1.001, 1.001)	(1.001, 1.001)	(1.001, 1.001)	(1.000, 1.001)
	DISABILITY	0.585***	0.585***	0.585***	0.585***
		(0.426, 0.804)	(0.426, 0.804)	(0.426, 0.804)	(0.426, 0.804)
Verbal	GENDER	0.540***	0.486***	0.422***	0.366***
		(0.526, 0.555)	(0.475, 0.497)	(0.404, 0.439)	(0.342, 0.391)
	AGE	1.000	1.038***	1.091***	1.147***
		(0.990, 1.010)	(1.029, 1.046)	(1.076, 1.106)	(1.121, 1.173)
	PARENTAL-Medium	1.035	1.078***	1.137***	1.200**
		(0.977, 1.097)	(1.026, 1.132)	(1.044, 1.239)	(1.044, 1.379)
		1.061**	1.151***	1.282***	1.429***

Language	PARENTAL-High	(1.004, 1.122)	(1.098, 1.206)	(1.182, 1.391)	(1.251, 1.631)
		1.001***	1.001***	1.001***	1.001***
	DISTANCE	(1.001, 1.001)	(1.001, 1.001)	(1.001, 1.001)	(1.001, 1.001)
		0.654***	0.654***	0.654***	0.654***
	DISABILITY	(0.494, 0.865)	(0.494, 0.865)	(0.494, 0.865)	(0.494, 0.865)
		0.688***	0.612***	0.568***	0.542***
	GENDER	(0.654, 0.724)	(0.570, 0.658)	(0.513, 0.628)	(0.479, 0.612)
		1.061***	1.046***	1.036*	1.030
	AGE	(1.039, 1.083)	(1.015, 1.077)	(0.994, 1.080)	(0.980, 1.083)
		1.040	0.887	0.801	0.751
	PARENTAL-Medium	(0.869, 1.245)	(0.693, 1.136)	(0.565, 1.136)	(0.494, 1.144)
		1.197**	1.194	1.191	1.190
	PARENTAL-High	(1.011, 1.418)	(0.950, 1.500)	(0.863, 1.645)	(0.806, 1.756)
		1.001***	1.001***	1.001***	1.001***
	DISTANCE	(1.001, 1.001)	(1.001, 1.001)	(1.001, 1.001)	(1.001, 1.001)
		0.259**	0.259**	0.259**	0.259**
	DISABILITY	(0.083, 0.804)	(0.083, 0.804)	(0.083, 0.804)	(0.083, 0.804)

The values in parentheses denote the limits of the 95% confidence interval. The symbols (*) indicates significance at the 10% level, (**) at the 5% level and (***) at the 1% level.

Note. The dataset belonging to the TurkStat and calculated by the author using R statistical software

Analysis of the estimated coefficients in the model in Table 4 confirms that the time-independent beginning risk ratio for the gender variable is statistically significant and less than 1 in all underlying models. Beyond statistical significance, the magnitude of this effect is highly substantive in practice: findings revealed that male students exhibit a comparatively lower risk of dropping out than female students in the early stages of higher education. Differences in this risk vary by academic field, representing a substantial relative risk reduction ranging from 31% in the Language model to 46% in the Verbal model, and around 40-41% in the Quantitative and Equal Weighted models. Meanwhile, another important finding is that the linear time interaction coefficient for gender is also less than 1 in all of the sub-models. Overall, this finding shows that, as time continues, male students' starting advantage does not disappear but stays strong, causing the risk gap to widen in the long term to the disadvantages of female students. This is consistent with the fact that, as of the 12th semester, the dropout risk for male students is lower than that for female students by 61% in the Quantitative model, 63% in the Equal Weighted model, 63% in the Verbal model and 46% in the Language model.

The increase in age at university entrance increases the risk of dropping out linearly in the early years and each annual increase in age raises the risk of leaving school in the early stages by 9% in the Quantitative Model and 6% in the Equal Weighted Model. While the time-interaction term for the age variable indicates a risk that continues or increases over time in the Quantitative, Equal Weighted, and Verbal models, the Language model represents an exception

in this matter. In the Language model, the starting risk linked to older age gradually decreases and stops being statistically significant in later periods. That means that, unlike their classmates in other areas, language learners actually see the initial struggles of joining the system later in life become less of an issue over time.

Submodel findings indicated that disability status had distinct effects on the cumulative risk of dropping out, differentiated by academic areas. The risk of university dropout among disabled students is considerably lower and statistically significant compared to their non-disabled peers in the Equal Weighted, Verbal and Language models. In the Quantitative model, however, disabilities were found to increase the initial dropout risk by 33%, and this effect is statistically significant at the 5% level. These findings suggest that students with disabilities who have achieved success in Türkiye's highly centralized selection examination system and enrolled in programs such as Verbal, Equally Weighted and Language programs have a high level of academic strength and motivation. The results can also be evaluated as a result of institutional programs of support at universities and the mechanisms of selection, which include quotas for students with disabilities. The analysis results, however, pointed to a requirement for additional institutional support systems to enable students to succeed in quantitative fields that may require laboratory work or extensive physical activities.

The variable of parental education level, analyzed in three groups according to Eurostat's International Standard Classification of Education (ISCED) aggregation (Eurostat, 2025), has presented results that are quite different from those reported in the general literature. Considering families with a low level of education as the benchmark, the early school dropout risk for students whose parents have a medium or high level of education shows differences depending on the field they decide to choose. This risk, however, is not smaller in the Quantitative and Verbal models when compared to the reference value for low educational level; on the contrary, it is bigger and grows as the duration of education rises. The situation is particularly evident in the Verbal model for students with highly educated parents; the relative risks for these students, which are 6% above the reference value in the beginning, reaches 43% by the twelfth period. In contrast, in the Equal Weighted model, neither medium nor high parental education levels exhibit a statistically significant relationship with the risk of dropping out in any period. The Language model, however, displays a different outcome: having a highly educated parent is connected to a statistically significant and important increase in the risk of dropping out at the very early stages of education; while the magnitude of this effect roughly remains constant, it disappears in subsequent periods. The effect of medium-level parental education is not statistically significant at any phase, despite a point estimate that declines over time. The presence of this unique case suggests that the dynamics of early school leaving in Türkiye differ across academic fields. Students from strong social support networks showed a higher initial risk of dropping out in verbal and language fields than their disadvantaged peers. In the long term, however, their patterns of behavior differ: in the quantitative and verbal fields, the chances of dropping out increase over time; in the language field, this initial high risk loses its statistical significance, while in the equal weighted field, parental education does not create a statistically significant difference in the risk of dropping out at any stage. Table 1's raw percentages may initially appear to suggest that a more educated parent is related to lower school dropout rates; however, when controlling for important factors such as types of entrance exam scores, age at enrollment, and university-specific differences, the actual conditional dynamics are revealed, and it is shown that a higher parental education level acts as an increasing risk factor in both quantitative and verbal models. It should also be emphasized that the existing administrative dataset does not enable direct observation of students' family

incomes, personal motivation, tendency to transfer to other programs or available alternative career opportunities in the labor market.

The distance between students' registered residence and the higher education institution where they are registered increases the initial risk of dropping out by a significant but practically negligible marginal amount in all models. While the p-values indicate high significance due to the massive sample, an SHR of 1.001 translates to a mere 0.1% increase in dropout risk per unit of distance. The fact that the interaction coefficient for distance stays at 1.001 shows that geographic distances and the underlying economic pressures they entail do not create added stress as the educational process progresses, but rather remain a steady and constant source of stress throughout the entire academic life.

The interdisciplinary heterogeneity among sub-models categorized by entrance exam types is clearly apparent. As displayed in the Cumulative Incidence Functions in Figure 1, the risk structures vary across fields of study. Descriptive analyses of past academic years have indicated that academic programs that consider Quantitative scores in their acceptance process exhibit a lower trend in dropout rates, in absolute terms, as compared to those that use Verbal and Language-based scores. The higher analytical skills of students who apply to Quantitative fields, and the high earning potential of these programs in the labor market, might encourage students' rational expectations for the future and thereby support their loyalty to the system. That said, it should also be pointed out that these structural differences noticed across disciplines may not stem just from the degree of difficulty of academic programs or labor market conditions; students may be choosing certain score types based on their hidden academic skills, personal confidence levels, and career targets.

To ensure the robustness of the analytical approach, a sensitivity analysis was carried out by estimating a standard Cox proportional hazards model that considers graduation not as a competing risk but simply as a censoring event (in the Appendix 2). The sensitivity analysis showed that the direction and statistical significance of key findings remained remarkably stable, including the gender advantage in favor of males, the protective effect of disability in non-quantitative fields, and the hypothesis that students whose parents are highly educated drop out of school voluntarily. In line with the methodological literature (Fine & Gray, 1999; Geskus, 2024), however, the standard Cox model systematically overestimated the magnitude of hazard ratios relative to competitive risks context. This sensitivity analysis not only verifies the robustness of the empirical findings but also confirms that the empirical necessity of modeling graduation as a competing risk exists in order to prevent upward bias in hazard estimates within the context of higher education in Türkiye.

Summary and Discussion

This study focused on the dynamics of dropout in Turkish higher education system, using approximately 2.9 million records filtered based on various criteria for cleaner data usage, derived directly from the administrative records of TurkStat (2026) higher education students database, beyond survey-based and limited-sample studies. The Fine-Gray approach, extended with time-varying coefficients, was adopted in the study, modeling students' university graduations as a risk competing with university dropout rather than a censoring mechanism, thereby eliminating biased estimates that might arise in standard survival analyses.

The findings of the analysis indicate that academic preparation level and field of study are among the most decisive factors in university completion. It was found that students whose scores were based on quantitative skills had a statistically significant lower risk of dropping out compared to those whose scores were based on equal weighted, verbal, and language skills.

This finding coincides with the previous observations that students in sciences where numerical qualities come to the fore, such as engineering and natural sciences, have lower dropout rates compared to the humanities, while it diverges from international contexts showing that engineering, mathematics, and natural sciences at the undergraduate level in Germany have the highest dropout rates. The fact that students in quantitative fields tend to start university with a stronger analytical basis and that these departments are highly valued in the labor market may have contributed to this situation by strengthening the expected benefit mechanism that increases students' willingness to stay in the system.

One of the most striking findings of the study, which diverges from the general consensus in the literature, is the effect of parental education level on the risk of dropping out. While some international studies argue that higher parental education reduces dropout risk, this study found that students whose parents are university graduates initially face a relatively higher risk of dropping out in certain fields; this risk increased dynamically over time in quantitative and verbal fields, while it lost its statistical significance in the language field and showed no significant impact in the equal weighted area. This situation can be explained by the good match theory and the concept of luxury dropout, or by the fact that completing their education may have become more essential for the future of students whose parents have relatively less education. Financial safety nets give students in high socioeconomic groups the option to leave programs that aren't a fit for them, whereas students from disadvantaged groups tend to stay in school because they view education as a chance to get a better life. Therefore, in the Turkish context, high parental education may trigger a strategic withdrawal in search of a better option rather than dropout, which is an indicator of failure. This said, the results need to be viewed with an understanding of the data's structural limitations. The broad categorization of parents' levels of education, while methodologically required to ensure the model's stability across a large administrative dataset, may mask significant heterogeneity within the categories. Unobservable variations within the broad group of highly educated cohorts, such as household wealth, cultural capital, or specific types of degrees, may influence students' duration of schooling in various ways. The findings thus appear to support the luxury school dropout hypothesis as a general structural trend; however, the aggregate nature of the variable makes it difficult to draw clear causal inferences regarding micro-level class dynamics.

Demographic variables showed that male students had a lower dropout risk than female students, which contradicts international literature suggesting that males have a greater risk of dropping out. This finding, however, aligns with the notion that women face higher risks due to the uncertainties associated with academic careers and the necessity of balancing family and work, as highlighted by Jaksztat et al. (2021). In the specific case of Türkiye, this situation can be explained by the social role pressure on male students to support their families and enter the workforce, which makes a university degree a necessity, and by the provision of mandatory military service delays for men in Türkiye.

The age variable, in line with other studies in the literature, shows that the risk of dropping out rises as the age of starting university increases, however, language-based programs present an exception where this initial risk decreases over time. Rising opportunity costs with increasing age and social incompatibilities resulting from generation differences with classmates contribute to older students leaving the system.

Findings concerning disability also offer a fresh perspective. In contrast to expectations, the risk of dropout among students with disabilities was found to be lower than that of their non-disabled peers in non quantitative fields, whereas it increased the dropout risk in quantitative fields indicate that physical disadvantages increase the risk of dropping out, the

results of this study suggest that individuals with disabilities who make it to university in Türkiye are a group that has undergone a high selection process and has above-average academic resilience and motivation.

It has been observed that the distance variable causes a statistically significant but limited increase in risk in terms of effect size, representing a constant marginal risk over time. This situation can be interpreted as a potential indicator that the costs of moving away from family and the benefits of on-campus integration balancing each other out.

Finally, it is necessary to consider the risk of omitted variable bias associated with the use of large administrative datasets. Control variables at the institutional level, while capturing some of the institutional heterogeneity, do not include variables such as students' academic performance, regional economic factors, or employment status at the time of registration. The lack of these factors, which are commonly associated with both socioeconomic status and the risk of dropping out, may influence coefficient estimates. The observed relationship between parental level of education and dropping out, for example, may be partially confounded by unobserved factors such as school quality or individual student motivation. To better identify the underlying mechanisms and further clarify the causal relationships identified in this study, future research will need to utilize linked datasets that integrate academic achievement records with labor market outcomes.

Conclusion

This study investigates the multi-dimensional characteristics of university dropout in the Turkish higher education using an inclusive administrative dataset containing approximately 2.9 million records. Using the Fine-Gray Competing Risks Model, extended with time-varying coefficients, this study overcomes the typical methodological restrictions that treat educational attainment simply as a censoring process and provides a clearer estimate of dropout dynamics. Results challenge common assumptions in the existing international studies and show the dropout in the Turkish context may be considered as a process mostly shaped by strategic decisions within the investigated subset, given that involuntary exclusions were omitted from the analysis. A major finding relates to the role of academic performance and the subject field chosen. Students admitted using quantitative score types displayed a lower risk of dropping out in comparison to their counterparts in verbal or equal-weighted fields. These findings are in line with the observations of Araque et al. (2009), which indicate lower dropout rates in quantitative fields, but they contradict some international findings, such as those of Behr et al. (2020), which highlight higher dropout rates in these fields in Germany. In the Turkish context, it can be attributed to the fact that students in quantitative fields generally possess a stronger analytical foundation, and the high value of these fields in the labor market strongly supports the desired benefits of the system.

Socioeconomic factors affecting school dropout rates in Türkiye display a considerable deviation from global patterns. Different from international studies (Aina, 2013; Pusztai et al., 2025) that point out that lower parental education is a big factor in the risk of dropping out, the study shows that after accounting for compounding covariates students with parents who have a college degree initially face a relatively higher risk of dropping out; a risk that increases dynamically in quantitative and verbal fields, while losing its statistical significance over time in the language field and having no significant effect in the equal weighted area. This finding is consistent with the luxury school dropout hypothesis suggested by Johnes and McNabb (2004) and Belloc et al. (2011). It implies that socio-economically advantaged students might have a higher tendency to voluntarily leave a program that does not meet their expectations

because they have potentially due to the financial security often associated with higher parental education levels. Disadvantaged students, on the other hand, see higher education as an important mechanism for social advancement and a better life, and therefore continue their studies, which means they are forced to finish the program.

Demographic analyses reinforce the fact that the situation in Turkish schools is unique. Male students initially have a lower dropout risk compared to female students, and this difference increases over time, leading to higher academic retention for males; this finding conflicts with general international findings that indicate higher dropout rates among males. These exceptions could potentially be related to local socio-cultural factors, while female students may increasingly face social pressures related to marriage and family formation as they age, male students may be encouraged by the expected role of providing for their families by participating in the workforce and the deferral of mandatory military service, which is granted only to actively registered males, though further research is needed to empirically test these specific mechanisms. In a similar way, school retention of students with disabilities, who are at lower risk of dropping out in non-quantitative fields, presents a challenge to the traditional view that physical disadvantages inherently make them more vulnerable in education (Rusmann et al., 2024). This finding points to the possibility that students with disabilities who are successful in the highly selective university admissions system may constitute a distinct group exhibiting above-average academic persistence and motivation, or they can take advantage of institutional support mechanisms aimed at encouraging them to continue their studies.

The analysis reveals that the likelihood of dropping out generally rises with age; however, language-based programs stand out as a notable exception, as the initial risk tends to decrease over time. The distance between a student's place of residence and the university constitutes a constant marginal risk throughout the student's academic life.

In conclusion, considering dropping out of university simply as an institutional or personal failure presents an incomplete and arguably misleading view. While direct motivations are unobserved in the administrative data, the empirical patterns are consistent with the hypothesis that school dropout is often a strategic decision aimed at exploring more advantageous socioeconomic or career prospects. Rather than focusing on broad and deficient interventions, policies aimed at retaining students should adopt a more targeted approach that takes into consideration various socio-economic, academic, and demographic variables that shape students' education choices.

References

- Aina, C. (2013). Parental background and university dropout in Italy. *Higher Education*, 65(4), 437–456. <https://doi.org/10.1007/s10734-012-9554-z>
- Aina, C., Baici, E., Casalone, G., & Pastore, F. (2022). The determinants of university dropout: A review of the socio-economic literature. *Socio-Economic Planning Sciences*, 79, Article 101102. <https://doi.org/10.1016/j.seps.2021.101102>
- Apumayta, R. Q., Cayllahua, J. C., Pari, A. C., Choque, V. I., Valverde, J. C. C., & Ataypoma, D. H. (2024). University dropout: A systematic review of the main determinant factors (2020-2024). *F1000 Research*, 13, Article 942. <https://doi.org/10.12688/f1000research.154263.2>
- Araque, F., Roldán, C., & Salguero, A. (2009). Factors influencing university drop out rates. *Computers & Education*, 53(3), 563–574. <https://doi.org/10.1016/j.compedu.2009.03.013>
- Bean, J. P. (1980). Dropouts and turnover: The synthesis and test of a causal model of student attrition. *Research in Higher Education*, 12(2), 155–187. <https://doi.org/10.1007/bf00976194>
- Becker, G. S. (1962). Investment in human capital: A theoretical analysis. *Journal of Political Economy*, 70(5, Part 2), 9–49. <https://doi.org/10.1086/258724>
- Behr, A., Giese, M., Tegui Kamdjou, H. D., & Theune, K. (2020). Dropping out of university: A literature review. *Review of Education*, 8(2), 614–652. <https://doi.org/10.1002/rev3.3202>
- Bellare, Y., Smith, A., Cochran, K., & Lopez, S. G. (2023). Motivations and barriers for adult learner achievement: Recommendations for institutions of higher education. *Adult Learning*, 34(1), 30–39. <https://doi.org/10.1177/10451595211059574>
- Belloc, F., Maruotti, A., & Petrella, L. (2011). How individual characteristics affect university students drop-out: A semiparametric mixed-effects model for an Italian case study. *Journal of Applied Statistics*, 38(10), 2225–2239. <https://doi.org/10.1080/02664763.2010.545373>
- Candelo-Meneses, L. M., Castro-Velasco, M. A., Periañez, C. A. H., & Castillo-Díaz, M. A. (2026). Factors associated with university dropout intention among health sciences students: The mediating role of academic burnout and satisfaction with education. *BMC Medical Education*, 26(1), Article 622. <https://doi.org/10.1186/s12909-026-08973-7>
- Curbani, F., Zanella, A., & Zibetti, A. W. (2026). A machine learning approach to predicting student dropout and supporting timely intervention. *Journal of Applied Research in Higher Education*, 1-18. <https://doi.org/10.1108/jarhe-07-2025-0538>
- di Biase, G., & Giusino, D. (2026). The Psychology of working students: A Scoping review. *Psychology International*, 8(1), Article 11. <https://doi.org/10.3390/psycholint8010011>
- Eurostat. (2025). *Glossary: Educational attainment level*. Eurostat Statistics Explained. Retrieved July 04, 2026, from https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:Educational_attainment_level

- Fine, J. P., & Gray, R. J. (1999). A proportional hazards model for the subdistribution of a competing risk. *Journal of the American Statistical Association*, 94(446), 496–509. <https://doi.org/10.1080/01621459.1999.10474144>
- Garza, A. N., & Fullerton, A. S. (2018). Staying close or going away: How distance to college impacts the educational attainment and academic performance of first-generation college students. *Sociological Perspectives*, 61(1), 164–185. <https://doi.org/10.1177/0731121417711413>
- Geskus, R. B. (2024). Competing risks: Concepts, methods, and software. *Annual review of Statistics and Its Application*, 11(1) 227 - 254. <https://doi.org/10.1146/annurev-statistics-040522-094556>
- Giraldo, A., Meggiolaro, S., Da Re, L., & Franceschini, C. (2025, October 24). *Modelling university career paths: A competing risks analysis of dropout and degree completion at the University of Padua*. Social Science Research Network <https://doi.org/10.2139/ssrn.5652271>
- Gonzalez, B., Mendes, T. P., Pinto, R., Correia, S. V., Albuquerque, S., & Paulino, P. (2025). Predictors of higher education dropout intention in the post-pandemic era: The mediating role of academic exhaustion. *PLOS One*, 20(7), e0327643. <https://doi.org/10.1371/journal.pone.0327643>
- Huynh-Cam, T. T., Chen, L. S., & Lu, T. C. (2025). Early prediction models and crucial factor extraction for first-year undergraduate student dropouts. *Journal of Applied Research in Higher Education*, 17(2), 624–639. <https://doi.org/10.1108/jarhe-10-2023-0461>
- Jaksztat, S., Neugebauer, M., & Brandt, G. (2021). Back out or hang on? An event history analysis of withdrawal from doctoral education in Germany. *Higher Education*, 82(5), 937–958. <https://doi.org/10.1007/s10734-021-00683-x>
- Johnes, G., & McNabb, R. (2004). Never give up on the good times: Student attrition in the UK. *Oxford Bulletin of Economics and Statistics*, 66(1), 23–47. <https://doi.org/10.1111/j.1468-0084.2004.00068.x>
- Kalbfleisch, J. D., & Prentice, R. L. (2002). *The statistical analysis of failure time data*. John Wiley & Sons. <https://doi.org/10.1002/9781118032985>
- Kasworm, C. E. (2010). Adult learners in a research university: Negotiating undergraduate student identity. *Adult Education Quarterly*, 60(2), 143–160. <https://doi.org/10.1177/0741713609336110>
- Kehm, B. M., Larsen, M. R., & Sommersel, H. B. (2019). Student dropout from universities in Europe: A review of empirical literature. *Hungarian Educational Research Journal*, 9(2), 147–164. <https://doi.org/10.1556/063.9.2019.1.18>
- Lizarte Simon, E. J., & Gijon Puerta, J. (2022). Prediction of early dropout in higher education using the SCPQ. *Cogent Psychology*, 9(1), Article 2123588. <https://doi.org/10.1080/23311908.2022.2123588>
- Mouganie, P. (2020). Conscription and the returns to education: Evidence from a regression discontinuity. *The Scandinavian Journal of Economics*, 122(3), 1112–1139. <https://doi.org/10.1111/sjoe.12361>

- Nurmalitasari, Awang Long, Z., & Faizuddin Mohd Noor, M. (2023). Factors influencing dropout students in higher education. *Education Research International*, 2023(1), Article 7704142. <https://doi.org/10.1155/2023/7704142>
- Opazo, D., Moreno, S., Álvarez-Miranda, E., & Pereira, J. (2021). Analysis of first-year university student dropout through machine learning models: A comparison between universities. *Mathematics*, 9(20), 2599. <https://doi.org/10.3390/math9202599>
- Oppedisano, V. (2011). The (adverse) effects of expanding higher education: Evidence from Italy. *Economics of Education Review*, 30(5), 997–1008. <https://doi.org/10.1016/j.econedurev.2011.04.010>
- Pedditz, M. L. (2024). School satisfaction and self-efficacy in adolescents and intention to drop out of school. *International Journal of Environmental Research and Public Health*, 21(1), 111. <https://doi.org/10.3390/ijerph21010111>
- Portela, A. C. T., da Silva, A. D., & Silva, G. O. (2021, July 11-16). Dropout and completion in the bachelor in statistics in Brazil: Use of survival analyses in a competing risk scenario. In *Proceedings 63rd ISI World Statistics Congress* (pp.711-714). International Statistical Institute. Retrieved January 17, 2026, from <https://isi-web.org/sites/default/files/import/pdf/194-day4-cps024-dropout-and-completion-in-the.pdf>
- Pusztai, G., Hrabéczy, A., & Csók, C. (2025). Parental involvement as an antidote to student dropout in higher education: Students' perceptions of dropout risk. *Open Education Studies*, 7(1), Article 20250089. <https://doi.org/10.1515/edu-2025-0089>
- Quimiz-Moreira, M., Delgadillo, R., Parraga-Alava, J., Maculan, N., & Mauricio, D. (2025). Factors, prediction, explainability, and simulating university dropout through machine learning: A systematic review, 2012–2024. *Computation*, 13(8), Article 198. <https://doi.org/10.3390/computation13080198>
- Russmann, M., Netz, N., & Lörz, M. (2024). Dropout intent of students with disabilities. *Higher Education*, 88(1), 183–208. <https://doi.org/10.1007/s10734-023-01111-y>
- Schoenfeld, D. (1982). Partial residuals for the proportional hazards regression model. *Biometrika*, 69(1), 239-241. <https://doi.org/10.1093/biomet/69.1.239>
- Sallai, G. M., Bahnson, M., Shanachilubwa, K., & Berdanier, C. G. (2023). Persistence at what cost? How graduate engineering students consider the costs of persistence within attrition considerations. *Journal of Engineering Education*, 112(3), 613-633. <https://doi.org/10.1002/jee.20528>
- Sestelo, M., Meira-Machado, L., Villanueva, N. M., & Roca-Pardiñas, J. (2024). A method for determining groups in cumulative incidence curves in competing risk data. *Biometrical Journal*, 66(4), Article 2300084. <https://doi.org/10.1002/bimj.202300084>
- Tinto, V. (1975). Dropout from higher education: A theoretical synthesis of recent research. *Review of Educational Research*, 45(1), 89–125. <https://doi.org/10.3102/00346543045001089>
- Tinto, V. (1988). Stages of student departure: Reflections on the longitudinal character of student leaving. *The Journal of Higher Education*, 59(4), 438-455. <https://doi.org/10.1080/00221546.1988.11780199>

- Turkish Statistical Institute. (2026). *Higher education statistics* [Data set]. TurkStat.
- Valencia-Arias, A., Valera Aredo, J. C., Valencia, J., Cardona-Acevedo, S., Patiño-Vanegas, J. C., & Uribe Bedoya, H. (2025). Key determinants of university dropout: Academic, economic, and psychosocial factors in student retention. *Frontiers in Education*, 10, Article 1701644. <https://doi.org/10.3389/feduc.2025.1701644>
- Venkatesan, R. G., Karmegam, D., & Mappillairaju, B. (2024). Exploring statistical approaches for predicting student dropout in education: A systematic review and meta-analysis. *Journal of Computational Social Science*, 7(1), 171-196. <https://doi.org/10.1007/s42001-023-00231-w>
- Vignoles, A., & Powdthavee, N. (2009). The socio-economic gap in university dropout. *The BE Journal of Economic Analysis & Policy*, 9(1), 19-39. <https://doi.org/10.2202/1935-1682.2051>
- Zeragaber, T. Y., Teame, G. T., & Tsighe, Z. (2024). Assessing the effect of home-to-school distance on student dropout rate in Adi-Keyih sub-zone, Eritrea. *International Journal of Educational Research Open*, 7, Article 100340. <https://doi.org/10.1016/j.ijedro.2024.100340>

Appendix

Appendix 1: Raw Coefficients and Time-Interaction Parameters of the Fine-Gray Models

Model	Coefficient	Main Effect: β (SE)	Main Effect: SHR(95% CI)	p-value	Time Int.: β (SE)	Time Int.: SHR(95% CI)	p-value
Quantitative	GENDER	-0.468	0.626	<0.001	-0.039	0.962	<0.001
		-0.016	(0.606, 0.646)		-0.003	(0.956, 0.969)	
	AGE	0.08	1.083	<0.001	0.005	1.005	<0.001
		-0.007	(1.069, 1.098)		-0.001	(1.002, 1.008)	
	PARENTAL-Medium	0.122	1.13	0.007	0.003	1.003	0.77
		-0.045	(1.034, 1.236)		-0.009	(0.985, 1.020)	
	PARENTAL-High	0.049	1.05	0.259	0.004	1.004	0.635
		-0.043	(0.965, 1.144)		-0.008	(0.988, 1.021)	
	DISTANCE	0.001	1.001	<0.001	0	1	<0.001
		0	(1.001, 1.001)		0	(1.000, 1.000)	
Equal Weighted	GENDER	0.283	1.327	0.044	-	-	-
		-0.14	(1.007, 1.747)				
	GENDER	-0.485	0.616	<0.001	-0.042	0.959	<0.001
		-0.014	(0.599, 0.633)		-0.003	(0.953, 0.965)	
	AGE	0.044	1.045	<0.001	0.011	1.011	<0.001
		-0.006	(1.034, 1.057)		-0.001	(1.008, 1.013)	
	PARENTAL-Medium	0.054	1.055	0.148	-0.013	0.987	0.065
		-0.037	(0.981, 1.135)		-0.007	(0.973, 1.001)	
	PARENTAL-High	0.011	1.011	0.757	-0.007	0.993	0.301
		-0.036	(0.943, 1.084)		-0.007	(0.980, 1.006)	
Verbal	DISTANCE	0.001	1.001	<0.001	0	1	<0.001
		0	(1.001, 1.001)		0	(1.000, 1.000)	
	DISABILITY	-0.536	0.585	<0.001	-	-	-
		-0.162	(0.426, 0.804)				
	GENDER	-0.581	0.56	<0.001	-0.035	0.965	<0.001
		-0.016	(0.542, 0.577)		-0.004	(0.958, 0.972)	
	AGE	-0.013	0.987	0.029	0.012	1.013	<0.001
		-0.006	(0.976, 0.999)		-0.001	(1.010, 1.015)	
	PARENTAL-Medium	0.021	1.022	0.538	0.013	1.014	0.077
		-0.035	(0.955, 1.093)		-0.008	(0.999, 1.029)	
Language	PARENTAL-High	0.032	1.033	0.328	0.027	1.027	<0.001
		-0.033	(0.968, 1.102)		-0.007	(1.013, 1.042)	
	DISTANCE	0.001	1.001	<0.001	0	1	0.107
		0	(1.001, 1.001)		0	(1.000, 1.000)	
	DISABILITY	-0.425	0.654	0.003	-	-	-
		-0.143	(0.494, 0.865)				
	GENDER	-0.286	0.752	<0.001	-0.128	0.88	<0.001
		-0.037	(0.699, 0.808)		-0.032	(0.826, 0.938)	
	AGE	0.07	1.072	<0.001	-0.016	0.985	0.234

		-0.015	(1.042, 1.103)		-0.013	(0.960, 1.010)	
	PARENTAL-Medium	0.16	1.174	0.214	-0.174	0.84	0.119
		-0.129	(0.912, 1.511)		-0.112	(0.675, 1.046)	
	PARENTAL-High	0.182	1.2	0.136	-0.003	0.997	0.976
		-0.122	(0.944, 1.524)		-0.104	(0.813, 1.223)	
	DISTANCE	0.001	1.001	<0.001	0	1	0.007
		0	(1.001, 1.001)		0	(1.000, 1.000)	
	DISABILITY	-1.351	0.259	0.019	-	-	-
		-0.578	(0.083, 0.804)				

Appendix 2: Sensitivity Analysis: Standard Cox Proportional Hazards Model Estimates

Model	Variable	Cox HR (95% CI)	p-value
Quantitative	GENDER	0.571 (0.560, 0.583)	<0.001
	AGE	1.128 (1.118, 1.138)	<0.001
	PARENTAL-Medium	1.127 (1.064, 1.194)	<0.001
	PARENTAL-High	1.047 (0.991, 1.107)	0.098
	DISTANCE	1.001 (1.001, 1.001)	<0.001
	DISABILITY	1.296 (0.984, 1.706)	0.065
Equal Weighted	GENDER	0.564 (0.554, 0.575)	<0.001
	AGE	1.080 (1.072, 1.088)	<0.001
	PARENTAL-Medium	1.002 (0.954, 1.052)	0.937
	PARENTAL-High	0.988 (0.943, 1.036)	0.622
	DISTANCE	1.001 (1.001, 1.001)	<0.001
	DISABILITY	0.576 (0.419, 0.792)	0.001
Verbal	GENDER	0.528 (0.517, 0.540)	<0.001
	AGE	1.021 (1.013, 1.030)	<0.001
	PARENTAL-Medium	1.066 (1.016, 1.118)	0.009
	PARENTAL-High	1.130 (1.080, 1.183)	<0.001
	DISTANCE	1.001 (1.001, 1.001)	<0.001
	DISABILITY	0.651 (0.492, 0.862)	0.003
Language	GENDER	0.690 (0.656, 0.726)	<0.001
	AGE	1.057 (1.036, 1.079)	<0.001
	PARENTAL-Medium	1.034 (0.865, 1.235)	0.715
	PARENTAL-High	1.217 (1.030, 1.439)	0.021
	DISTANCE	1.001 (1.001, 1.001)	<0.001
	DISABILITY	0.261 (0.084, 0.812)	0.02

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The author declared that the ethical rules for research and publication were followed while preparing the article.

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