



Modelling of Distance Learners' Retention Using Mixed-Model on Non-Proportional Hazard

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Abstract

Universitas Terbuka is a public university in Indonesia that implements an open-distance education system. The quality and success of higher education in Indonesia are indicated by the gross enrolment rate (GER). Modelling student retention is one indicator of the value of the GER. The chances of distance learners' retention in a certain period can be determined through survival analysis, namely the "Cox model" or "Cox proportional hazard model". The limitations of the Cox model pose new problems in modelling that involve more than two types of covariates and the presence of random effects. The problem that arises is the non-proportional hazard. The cause of non-proportional hazard is time-dependent covariates, so that individual risk changes over time. Another reason is the presence of random effects, both observed and unobserved. In this model, there are two random effects, namely, the unobserved random effect and the observed random effect. Thus, the model is called the mixed effect model of non-proportional hazard. Based on the characteristics of the covariates observed, appropriate survival analysis for modelling distance learners' retention is a mixed model on the non-proportional hazard. The covariates involved in very complex modelling include time-independent covariates, time-dependent covariates, and unobserved random effects. The results of the analysis with the mixed model on non-proportional hazard showed that the covariates that significantly affected the distance learner's retention were: educational background, age, grade point average, marital status, scholarship, independent learning culture, number of credits taken, and number of courses taken each semester.

Keywords: Universitas Terbuka; distance learners' retention; analysis survival; mixed model on the non-proportional hazard

Introduction

In the era of globalisation, people are required to achieve more knowledge to be able to compete nationally. Higher education is a priority everywhere, including in Indonesia. However, distance and time sometimes become obstacles to accessing education. In Indonesia, most regions consist of islands and communities whose heterogeneity creates problems in access to education. To overcome this problem, a network system-based education system is needed.

Universitas Terbuka has a distance education system that was established by the government to overcome problems in access to education. The presence of UT is significant for enabling the people of Indonesia, most of whom are in the archipelago and in the 3T (underdeveloped, frontier, and outermost) regions, to be able to receive higher education.

Providing the option of studying by distance education was the government's attempt to increase the gross enrolment rate (GER) of higher education. Gross enrolment shows the success of higher education in Indonesia. The GER of higher education can be seen from modelling

distance learners' retention. This model is essential for UT to preserve the sustainability of students for the complete study.

Data (ICT-UT, 2015) and several studies conducted by Ratnaningsih et al. (2008), Rahayu (2009), Ratnaningsih (2011), and Ratnaningsih et al. (2018) showed that the percentage of non-active UT students was still high. Non-active students are those who do not register for four semesters in a row. Rahayu revealed that UT's method of handling non-active students is still felt to be less effective and efficient because it does not consider the students' characteristics. Besides, the achievement of learning outcomes shown by the cumulative grade point average (GPA) is still low (Soleiman, 1991; Kadarko, 2000; Darmayanti & Belawati, 2002; Ratnaningsih et al., 2008).

Retention data related to the time, or analysis of time of the event. Low student retention can lead to dropping out (failure to complete studies). We define student retention as a condition in which students can complete their studies when they are registered continuously per semester (Arifin, 2018; Belawati, 1998; Berger & Lyon, 2005; Sembiring, 2014). The distance learners' retention modelling of UT students uses appropriate survival analysis based on such data conditions.

Student retention is one indicator of institutional accountability in the implementation of educational programs, including distance education. The factors that influence student retention in distance education are very complex and varied. In general, these factors can be grouped into individual factors, internal factors, and external factors. In modelling, these factors can function as covariates. Covariates that affect student retention can be grouped into time-dependent covariates, time-dependent covariates, and random effects.

The problem of student retention can be seen as a matter related to time, or time of an event. Low student retention can lead to dropping out of college or failure to complete studies, which can be seen as a failure time. Statistical analysis for modelling failure time or survival time is survival analysis. The Cox model is the best model for analysing survival time. However, the Cox model is often inadequate in its application because many covariates are involved. Likewise, student retention. Based on these two problems, the development of an incomparable risk model is necessary.

The application of survival analysis when modelling distance learners' retention has not been widely studied, especially mixed model non-proportional hazard. Using the mixed model non-proportional hazard is indispensable because UT students' retention data involves multiple covariates and the presence of two random effects. The mixed model non-proportional hazard is expected to be useful for policymakers at UT to be able to maintain the gross enrolment rate (GER) of students as an indicator of the quality and success of higher education in Indonesia.

Selected literature review

Survival analysis

Survival analysis is a statistical method used to analyse data in the form of *time until the occurrence of an event*. Events can include death, recovery, recurrence, failure of study, or other events determined by the researcher. In survival analysis, subjects are usually followed over a specified period, with the focus being on the time at which the event of interest occurs. The survival time is the observation period, or the time until the occurrence of the desired event. The purpose of survival analysis is to determine the relationship between the incident and the explanatory variables measured at the time of the study. McCullagh and Nelder (1983) suggest that the main purpose of survival analysis is to analyse the data that is always positive in the

measuring scale, with a long-distance interval between the initial and final data. The data type in survival analysis is the time from a certain point until a failure happens.

There are three important elements in determining survival time: time origin, the definition of failure time (which must be clear), and the time scale as a unit of measurement. The difference between survival analysis and other statistical analyses is the existence of censored data. Observations are “censored” when the information about their survival time is incomplete. Dobson (2002) stated that the causes of censored data are the loss to follow-up (which occurs when the object moves, dies, or refuses to participate), dropout (which occurs when the treatment is stopped for some reason), and termination (which occurs at the end of the study when the objects have not reached the failure event).

Cox model

The Cox model (developed by David Cox) is a semiparametric regression model in survival analysis. Many studies in a variety of fields use this model. It is often used to estimate the association between covariates and a potentially censored failure time, and to predict the relative risk of failure. This model assumes that the individual’s risk to other individuals is constant over time, and the individual is homogeneous. Suppose survival data are available on x characteristic of individuals in period t , and denoted as $h(t, X)$. The baseline hazard function is denoted as $h_0(t)$, and b^T is a coefficient vector of regression.

The Cox model formulation is:

$$h(t, X) = h_0(t) \exp \left(\sum_{i=1}^p \beta_i X_i \right) \text{ where } X = X_1, X_2, \dots, X_p.$$

The Cox regression model states the hazard level of individuals with specific characteristics called covariates (Cox & Oakes, 1984). Jones and Branton (2005) use Cox regression to determine the policy of setting or disseminating studies using hazard ratio.

Mixed model on non-proportional hazard

A mixed model on non-proportional hazard is the outgrowth of the Cox model that has been developed by Ratnaningsih et al. (2018), who called this a “stratified-extended with frailty” (SEF) model. The SEF model was developed to overcome non-proportional hazard. The causes of non-proportional hazard are time-dependent covariates and unobserved random effects (known as “frailty”).

The main principle of frailty as suggested by Vaupel et al. (1979) and Wienke (2011), is that each individual has different risks for surviving a disease. Weak (frail) individuals will not be able to last as long as strong individuals. In the case of cancer, frailty can relate to a hospital’s culture, genetic factors, diet patterns, or the patient’s medical record. In distance education, frailty can involve a culture of independent learning, motivation to learn, management of study time, learning resource facilities, academic track records in tutorials, and environmental factors.

The model SEF formulation is:

$$\lambda_s(t, \mathbf{x}) = \lambda_{0s}(t) \exp \left(\sum_{a=1}^{p_1} \beta_{ai} x_{ai} + \sum_{b=1}^{p_2} \alpha_{bi} x_{bi}(t_j) + v_s \right).$$

Where:

- s = the order of stratum; $s = 1, 2, \dots, m$
- $\lambda_{0s}(t)$ = baseline hazard function on each stratum
- β_{ai} = fixed effect coefficient vector for covariate number a of individual number i
- x_{ai} = time-independent covariate (fixed effect) number a of individual number i
- α_{bi} = coefficient vector for time-dependent covariate number b of individual number i
- $x_{bi}(t_j)$ = time-dependent covariate of individual number i at time t_j
- v_s = frailty on stratum number s .

Distance education

The distance education system has two main components: distance learning and distance teaching (Keegan, 1993). The distance learning component focuses on students and the learner-centered process, while the distance teaching component focuses on the teaching process, organisational systems, and instructors (teacher and system centred). Distance education focuses on students and their learning processes, the teaching process, organisational systems, and instructors.

Universitas Terbuka applies the distance education system. The term “long distance” means that learning is not face to face—it uses print (modules) and non-print media. Students who are far from UT’s learning centre can still follow the learning process by using the media that is best suited to their characteristics and those of the course.

Figure 1 shows a model of the learning process at UT as described by Winataputra and Ratnaningsih (2006). The model shows that independent learning and tutorials play an essential role in the learning process. In distance education, the primary milestone of the learning process is independent learning (Winataputra & Ratnaningsih, 2006; Ratnaningsih, 2013).

Because UT can reach all levels of society throughout the country, it can reach the 3T areas. At present, UT has 39 representative offices across Indonesia, and one unit in the Foreign Service office which has served students in 50 countries. These representative offices are called Open University Distance Learning Units.

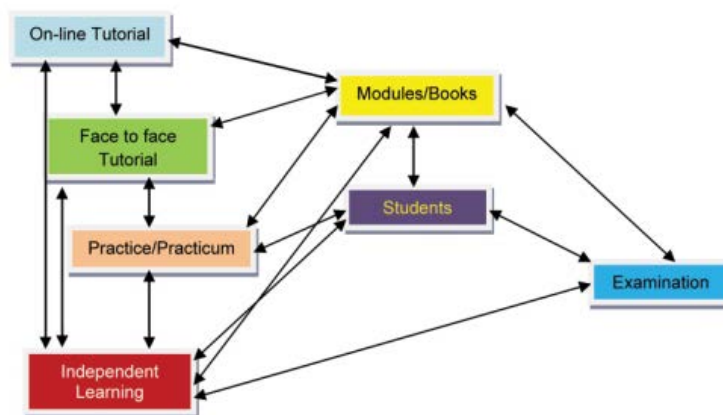


Figure 1 Model of the learning process at UT

The characteristics of distance education learners

The characteristics of distance education learners are unique and diverse. Schuemer (1993) suggests that, in the distance education system, the student learning process is more complicated. Generally, students are mature, working, and have a family. Their motivation to attend lectures in the distance education system is very diverse.

The results of research in several countries regarding student retention factors show that age, GPA, credit hours, courses, marriage, and employment affect student retention. Andriani and Pangaribuan (2006), Xenos et al. (2002), and Pierrakeas et al. (2004) in Greece state that there is a correlation between the age of distance learners and “dropping out”. Age affects the readiness and ability of independent student learners.

Schuemer (1993) and Rovai (2003) stated that, in general, the factors that led to distance education students dropping out of study included advanced age, lack of study time, difficulty in accessing the internet, lack of feedback from tutors, work, family, external stimulation, and personal financial problems. Coggins (1989) also suggests that one cause of the high dropout rate is the student’s educational background.

Several studies have also shown that GPA has a profound effect on student retention and is a determinant of the sustainability of university studies. Soeleiman (1991), Ratnaningsih (2008), McCormic & Lucas (2014), Klapproth & Schaltz (2014), Gaytan (2015), and Boton and Gregory (2015) all cite the academic characteristics of students as determinants of dropping out. The credit load taken on by students is another factor. Cambruzzi et al. (2015) in Brazilia stated that many students dropped out of school because the credit load did not match students’ ability. Allen et al. (2016) stated that many students in the United States dropped out because they took on too much course material, but had paid for tuition.

Research method

The research data used is the retention data of UT students who first registered in Semester 1, 2008, and extended until Semester 2, 2015. The response variable is survival time measured in semester units. Survival time is the number of semesters registered by students in the research period (16 semesters). In this research, the event is a non-active student. Observations are “censored” when the information about their survival time is incomplete. In this research, censored data (categorised as 0) is students who are active or have graduated. “Uncensored” (categorised as 1) are non-active students.

In this study, covariates that affect learners’ retention in UT were grouped as a fixed effect and a random effect. The fixed effect of covariates is categorised as time-independent covariates and time-dependent covariates. Time-independent covariates are educational background, gender, age, marital status, employment status, and home area. Time-dependent covariates are the number of credits taken and the number of courses registered per semester.

An unobserved random effect is a frailty. The frailty is identified with the culture of independent learning, learning motivation, management of study time, learning resource facilities, academic track record in tutorials, and environmental factors. The frailty is assumed to follow a normal distribution, with mean=0 and variance=5.

Modelling of distance learners’ retention uses the SEF model (Equation 1) with a generalised mixed-model linear approach. The software used is R using the frailtyHL package (Ha et al., 2018).

Result and discussion

The description of UT student retention data is based on demographic and academic characteristics. Student demographic characteristics include residence, gender, student age, marital status, and employment status. Academic characteristics include formal educational background, courses of interest, GPA, number of credits taken, and number of courses taken.

In this study, 4483 UT students were observed from 10 study programmes. The percentage of censored and uncensored data is shown in Figure 1. Figure 2 shows that the percentage of UT students who are censored is as high as 35%, while the non-censored rate is 65%. On the other hand, as many as 65% of UT students are non-active. This means the percentage of UT non-active students is very high.

Figure 3 shows that, based on age, the percentage of UT students who are not censored (non-active students) is as high as 77.17%, and are <35 years old. Meanwhile, from Figure 4 it can be seen that, in general, UT non-active students are those who have a GPA > 2.0 (84.93%), the number of courses registered is more than 8 per semester (96.12%), the number of credits <75 (97.95%), and 81.25% have a bachelor's degree.

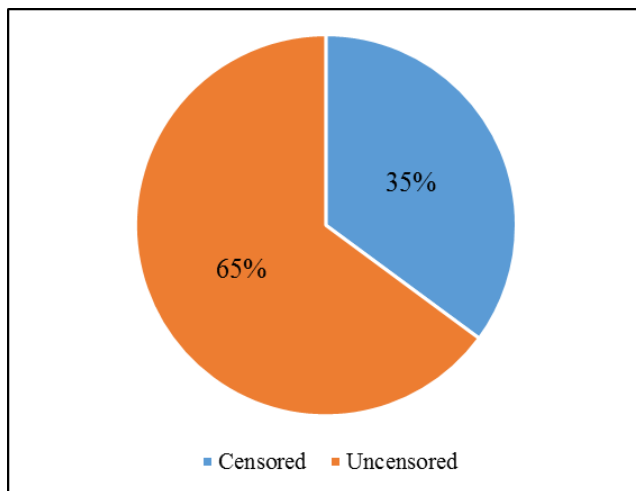


Figure 2 Percentage of UT students based on censored

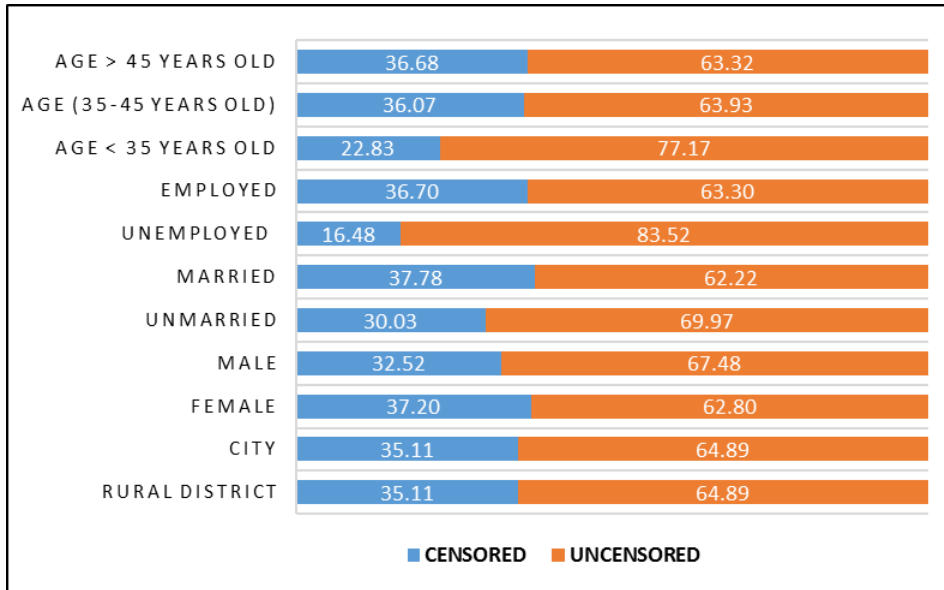


Figure 3 Characteristics of UT students based on demographics and censored

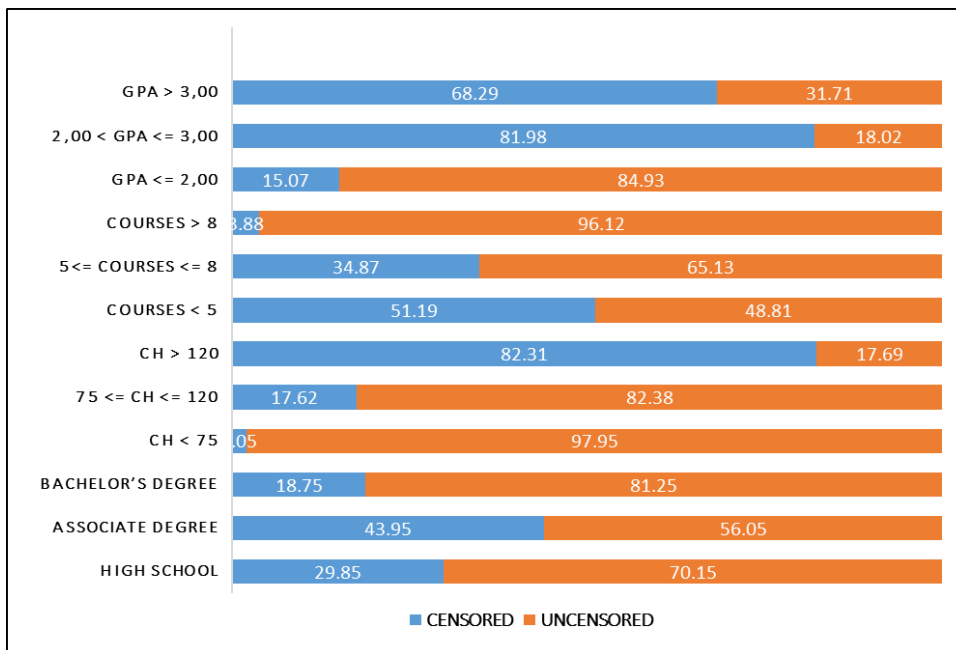


Figure 4 Characteristics of UT students based on academic and censored

Time-independent covariates that affect learners' retention are educational background, study programs that are in demand, gender, age, marital status, employment status, and home area. Meanwhile, the time-dependent covariates that affect learners' retention are the number of credits taken, the number of courses registered per semester, and the GPA. The results of the analysis of the SEF model on UT student retention are presented in Table 1.

Table 1 Statistics resulting from the analysis using the SEF model

Observed covariates	Estimate	Std. error	HR	t-value	p-value
Edu. background=2	0.2023	0.0516	1.2243	3.9226	8.76E-05
Edu. background=3	0.7080	0.2123	2.0300	3.3349	8.53E-04
Age	-0.1153	0.0443	0.8911	-2.6053	9.18E-03
Home area	0.0062	0.0520	1.0062	0.1197	9.05E-01
Gender	0.0480	0.0404	1.0492	1.1884	2.35E-01
GPA	-0.9678	0.0391	0.3799	-24.7564	2.64E-13
Employment status	-0.0417	0.0687	0.9591	-0.6078	5.43E-01
Marital status	-0.0860	0.0481	0.9176	-1.7863	7.41E-02
Scholarship	0.1771	0.0838	1.1938	2.1136	3.46E-02
Credit hours	-0.2260	0.0067	0.7977	-33.6305	6.02E-20
Courses	-0.0768	0.0124	0.9261	-6.1771	6.53E-10

The parameter estimation of random effect (v) generated by SEF consists of mean = 0.01732 and standard error = 0.007927. The standard error is a measure of the distribution of the average sample to the population average. A relatively small standard error indicates the average error or deviation of the parameters of the population. From the size of the parameter estimation, it can be stated that the SEF model is quite adequate, and the SEF model can be used as an alternative model for distance learners' retention.

The difference in deviation between SEF models with and without frailty is a measure that the model has a significant effect. In this study, the difference in the deviation between the two models is 3.188. This value is higher than the critical value (2.71), so frailty has a significant influence on the modelling of distance learners' retention. In the case of UT, frailty can be associated with an independent learning culture, academic records in online tutorials, learning motivation, management of study time, learning resource facilities, ownership of teaching materials, and environmental factors. All these conditions are, of course, different for each student, so have a different influence on learning success. Thus, to improve service quality, "frailty" needs to be considered by UT to increase student retention. When developing programmes, UT must pay more attention to the influence of this "frailty" to improve services for students.

The results of the analysis show that the statistically significant covariates with an alpha level of 10% are educational background, age, GPA, marital status, scholarship, credit hours completed, and the number of courses taken per semester. This result corresponds with several kinds of research on distance education in countries such as Indonesia, Greece, Nigeria, Brazil, Iran, the United Kingdom, Germany, and Turkey.

Universitas Terbuka students who hold an associate's degree and a bachelor's degree have better survival rates than high school graduates. This finding corresponds with Coggins' (1989) finding that one of the causes of the high dropout rate in a distance learning system is the student's educational background. Likewise, Thomas et al. (2014) observe that educational background has an effect on academic performance in internet-based distance learning—in both non-formal and formal educational institutions. The hazard ratio shows that students who have a diploma education background can have a retention of 1.22 times, while those with an undergraduate education background can have a retention of 2.03 times more.

Age also has a significant influence on the modelling of the students' survival data. The analysis results show that the parameter estimation for age is negative. It suggests that a higher dropout rate occurs among younger students (< 35). This means they tend to have lower survival capability in their course of study than their older counterparts. This particular finding corresponds with those reported in studies by Andriani and Pangaribuan (2006), Kadarko (2000), and Pierrakeas et al. (2004). Pierrakeas et al.'s study was conducted in Greece: the other two were conducted in Indonesia. Andriani and Pangaribuan (2006) demonstrate that age contributes to the level of readiness and competence for undertaking independent learning. Kadarko (2000) reveals that age has had a tangible effect on the variations of self-directed learning skills. Pierrakeas et al. (2004) find that younger students (< 30 years old) are more likely to drop out. The hazard ratio of age was 0.89. This means that students over the age of 35 have a learning retention of 0.89 compared with those aged less than 35 years.

As for GPA, its parameter estimation indicates a negative coefficient. The value signifies that students with lower GPAs are much more likely to drop out, which means their survival in completing their studies is low. This finding corresponds with those of studies carried out by Soeleiman (1991); Ratnaningsih (2008); McCormick and Lucas (2014); Klapproth and Schaltz 2014; Gaytan (2015); and Boton and Gregory (2015). They report that GPA is a significantly influential factor in student retention, and it is a determining factor in a student's study progress in higher education. In general, a student's academic characteristics do, indeed, contribute to dropout tendency among university students. The hazard ratio of GPA shows that students who have a low GPA have a chance of dropping out of university 0.38 times more than students who have a high GPA.

Marital status also has a negative estimation coefficient. The value reflects a tendency for married students to have a generally lower survival rate in their course of study than unmarried students. This finding corresponds with those of researchers Schuemer (1993) and Rovai (2003). They affirm that some factors that contribute to dropout among students attending distance education institutions are mature age, inadequate time for study, lack of skill in accessing the internet, lack of feedback from the tutors, demanding job responsibilities, family issues, external stimulation or distraction, and personal financial problems. The hazard ratio shows that married students are likely to drop out of college 0.92 times more than unmarried students.

Scholarships have a positive influence on student learning retention. Awards can increase learners' retention. Students who get scholarships tend to survive well—an award can motivate students to learn. This is especially so for students who are in the 3T (frontier, outermost, and disadvantaged) categories. Scholarships can help these students to access higher education. Students who get awards have 1.2 times the learning retention of students who do not receive scholarships.

The number of courses taken per semester and the number of credit hours completed also indicate negative values. These results suggest that students who take many classes (and therefore have a high number of credit hours each semester) tend to have a lower survival rate. A study conducted by Cambuzzi et al. (2015) in Brazil presents a similar case. For instance, at an institution that set a standard of 12 credit hours for its students to complete for each semester, some students chose to take 20 credit hours per semester with the assumption that in doing so, they would finish their studies faster and that the workload in a distance learning system would not be too hard to deal with. Allen et al. (2016) in the United States said that many students took courses, paid for tuition, and then dropped out. The hazard ratio for the number of courses registered per semester is 0.93. That is, students taking classes in more than eight subjects have low learning retention of 0.93 times compared with students who take less than eight courses.

Conclusion

Distance education plays an essential role in increasing access to higher education. Universitas Terbuka is one university in Indonesia that implements distance education. The University's existence is significant—it has a strategic role in increasing access to higher education and improving the quality of human resources capable of competing globally.

Indicators of the success and quality of higher education in Indonesia can be seen in the gross enrolment rate. One way to increase these rates is to look at student retention modelling. Likewise, UT, as an organiser of distance education, needs to conduct a study of UT student retention modelling. This modelling is very complex, so adequate analysis is needed. Mixed models on non-proportional hazards (such as the SEF model) can be applied at UT because this modelling involves several covariates that have both fixed and random effects.

The results of the analysis with the SEF model indicate that frailty has a significant influence on UT student retention modelling. In reality, frailty is associated with an independent learning culture, academic records in online tutorials, learning motivation, management of study time, gaining resource facilities, ownership of teaching materials, and environmental factors. UT needs to pay serious attention to these components if it is to improve learning services.

Other covariates that influence UT student retention modelling are educational background, age, marital status, scholarship, number of credits taken, and number of courses registered per semester. This condition is also evident in several other countries that implement distance education. The hazard ratio value indicates the risk level of each covariate for modelling.

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