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GRADE POINT AVERAGE: A GOOD PREDICTOR OF STUDENT DROPOUT IN UNIVERSITAS TERBUKA INDONESIA

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Abstract

Dropout rates in university that uses distance learning methods are definitely higher than those in conventional universities, including at Universitas Terbuka (UT) Indonesia. The term “drop out” is called non-active student in UT. This research aims to investigating the best time to identify students who become non-active and the student characteristics that have a higher risk of being non-active in distance learning. The data used in this study was provided by UT's Academic Information System Database (secondary data). Email surveys collected additional data. Logistic regression analysis was performed to identify students that are likely to drop out by Sociodemographic characteristics and their academic performance of students. This study reveals that grade point average (GPA) is an excellent predictor to identify students becoming non-active, especially in the first semester. We need to monitor student GPA throughout the first semester to prevent non-completion of their study, and it will improve the prediction accuracy.

Keywords: distance learning, dropout, GPA, non-active student, Indonesia.

1 INTRODUCTION

Online learning in higher education has become popular recently, especially after the COVID-19 pandemic. The main problem that is still a challenge in online learning is the high dropout rate (Mubarak, Cao, & Zhang, 2022). It is known that the dropout rates in university that uses online learning methods are definitely higher than those in conventional universities (university with face-to-face learning). A study showed that the student persistence rate in open universities is 10-20% lower than in conventional universities, with only 50% of the student completing their study (Carr in Rovai, 2002). The problem of the high rate of student dropout also becomes a primary concern for Indonesia Open University (in Indonesian: Universitas Terbuka or UT), Indonesia’s only public university that implements distance education. The term “dropout” is called non-active students in UT. Students are classified as non-active if they do not register for four consecutive semesters. The previous study showed that the percentage of non-active students in UT is quite high (42%) (Utami, Winarni, Handayani, & Zuhairi, 2020; Ratnaningsih, 2011). Based on the Universitas Terbuka's annual data, it is known that the number of active students as of 22 May 2022 is 346,584 (Universitas Terbuka, 2022). Compared to active students in 2015, the number decreased by 12.6% (Universitas Terbuka, 2015).

In general, dropout is caused by professional, academic, health, family, behavior, and individual reasons (Xenos, Pierrakeas, & Pintelas, 2002; Kotsiantis, Pierrakeas, & Pintelas, 2003; Mubarak, Cao, & Zhang, 2022). Specifically, some studies showed that demographic characteristics (e.g.,

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age, gender, educational background in high school, & employment status), classroom characteristics (e.g., course difficulty), cognitive engagement (e.g., exercise, seeking help, studying on weekends), and behavioral engagement (e.g., interaction in the online tutorial) are contributing factors for students being drop out (Ratnaningsih, 2011; Saefuddin & Ratnanningsih, 2008; Park & Choi, 2009; Sembiring, 2014; Sembiring, 2015; Coussement, Phan, De Caigny, Benoit, & Raes, 2020). Furthermore, academic performance data serve as a good predictor and most important variable of dropout (Ortiz-Lozano, Rua-Vieites, Bilbao-Calabuig, & Casadesús-Fa, 2020; Coussement, Phan, De Caigny, Benoit, & Raes, 2020).

The high number of non-active student at UT need to be solved. One of the good strategies to reduce non-active students is to identify its predictors. Many existing studies found the variables to predict student dropout in distance learning, but a limited number of studies identify the time when students become drop out. Our study focused on investigating the best time to identify students who become non-active and the student characteristics that have a higher risk of being non-active in distance learning.

2 METHODOLOGY

2.1 Study Design

This research is a retrospective cohort study. We used data obtained from the Academic Information System Database of Universitas Terbuka. The data selected were data from students of the biology study program, who registered for the first time from 2012 to 2014, then observed student re-registration status in each semester until the end of 2017. The selection of data in the biology study program is based on the consideration that it has a relatively low number of students with a high percentage of non-active students (47%). Data collection for the past few years was carried out to ensure the status of each student observed could be categorized as an active or non-active student at the time the research was conducted. As previously mentioned, students are categorized as non-active students if they did not register for four consecutive semesters. So the minimum observation time required is three years.

2.2 Data Collection and Analysis

The research data is secondary data taken from the student registration database, which includes information about the student’s name and identification, age, gender, employment status, previous educational level, grade point average, and the time of registration. In our study, the data of students’ status are grouped as active and non-active based on the last observation we performed. Non-active status is classified as an event, and the student's registration date before being non-

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active is categorized as an event date. All the variables analyzed in this study are presented in Table 1.

Table 1. Description of Variables Used in This Study.

Variable	Description
Age	Age at the time of registration, categorized into three groups: less than 35, between 35 to 45, and more than 45 years of age.
Gender	Men or Women
Employment Status	Employed or Unemployed
Previous Education Level	The level of school that student have completed before applying Universitas Terbuka, categorized as bachelor, diploma, and high school.
Grade Point Average	This variable is classified in to three categories, namely the students with GPA more than 3.00, between 2.00 and 3.00, and less than 2.00

The data is analyzed using STATA SE12.0 (College Station, TX). Descriptive analysis was carried out on categorical data using frequency distribution. Kaplan-Meier analysis was used to identify the mean time between failure on non-active students (missing data/data missing will become sensors in this analysis). Cox proportional hazard model analysis was performed to identify students that are likely to be non-active by the sociodemographic characteristics and academic performance of students. The result obtained from this analysis is a crude hazard ratio (HR) and p-value with a confidence level of 95%. Further analysis was performed using cox regression. The p-value limit included in the multivariate analysis is less than 0,25, and variables with a p-value of $<0,25$ were analyzed into one cox regression model using the backward elimination method. Significant variables are variables that have a p-value $<0,05$ after being diagnosed in each model. In the final model, the adjusted hazard ratio is obtained to determine the magnitude of the influence of independent variables on non-active students. The data fit the proportional-hazards assumption with p 0.7037 ($p>0.05$).

3 FINDINGS AND DISCUSSION

The number of students registered in UT's Biology Department in the period of 1st semester of 2012 to 2nd semester of 2014 is 354, with 198 (56%) categorized as active and 156 (44%) as non-

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active. Student characteristics are presented in Table 2. The majority (77%) of non-active students are less than 35 years old/ y.o., more than half (55%) are women, 67% of students are unemployed, and most students (89%) had previous education levels in high school. Based on student academic performance, most of the students (87%) had a grade point average (GPA) less than 2.00.

Table 2. Characteristics of the Student in Biology Department.

Student Characteristics	Non-active student (n=156)	Total respondent (n=354)
Sociodemography		
Age (years old)		
< 35	120 (77%)	281 (79%)
35-45	31 (20%)	63 (18%)
>45	5 (3%)	10 (3%)
Gender		
Female	86 (55%)	200 (57%)
Male	70 (45%)	154 (43%)
Employment		
Unemployed	104 (67%)	225 (64%)
Employed	52 (33%)	129 (36%)
Previous education level		
Bachelor	5 (3%)	6 (2%)
Diploma	12 (8%)	48 (13%)
High School	139 (89%)	300 (85%)
Student Academic Performance		
Grade Point Average		
>3.00	0 (0%)	20 (6%)
2.00-3.00	21 (13%)	111 (31%)
<2.00	135 (87%)	223 (63%)

There were 44% of non-active students from a total sample of 354 students during the observation period from 2012 to 2017. Moore and Kearsley (1996) stated that the percentage of 30% to 50% of non-active students in distance learning is categorized as a common condition. However, the percentage can be the main concern for UT, especially for Biology Department, and also the

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Faculty of Science and Technology has a lower number of students compared to other faculty at UT. Moreover, a study showed that non-active students can lead to a higher dropout rate (Ratnaningsuh, 2011), thus can potentially reduce the number of students in UT's Biology Department. Therefore, it is important to solve this by, among many other solutions, giving extra motivation for Biology student to finish their study. Based on the Kaplan-Meier analysis of all students, the incidence rate of non-active students in distance learning was 8.7 per 100 people per semester. The median time of this data was undetected, but only 25% of students who remain studied according to 1-semester observation (Table 3, Figure 1, and Figure 2). It means that 75% of students become non-active in the first semester. This study shows that the first semester is a critical period for students in UT's Biology Department to become non-active. This finding is similar to another study in Brazil's Open University, in which 85% of students withdraw from their studies during the initial semesters (Rodrigues de Oliveira, Aparecida Oesterreich, and Luci de Almeida, 2018; Ortiz-Lozano, Rua-Vieites, Bilbao-Calabuig, & Casadesús-Fa, 2020). Some of the main causes of student's dropout are time constraints, heavy workload and schedule in their job, and problems in utilizing technology and adapting learning methods in the distance education system (De La Varre et al., 2014; Rodrigues de Oliveira, Aparecida Oesterreich, and Luci de Almeida, 2018).

The high number of non-active students during initial semesters must be addressed accordingly, and this study reveals that the first semester is the best time to identify the student who is at risk become non-active. So, one good strategy to reduce the high number of non-active students is to improve academic monitoring and throughout the first semester. In addition, we can strengthen academic interaction between tutors and students through the provision of learning services, particularly in the first semester. Thus, students in the early program of distance learning, which is known as a new learning system for most students, are able to understand and adapt to the learning system. In addition, an increase in understanding of distance learning needs to be strengthened by specific introductory courses or class sessions commonly applied to all new students.

Table 3. Median time of non-active student.

Status of student	Incidence Rate	No. of subject	Survival Time (semester)		
			25%	50%	75%
Active	0	198	.	.	.

Non-active	0.5842697	156	1	1	2
Total	0.0877884	354	2	.	.

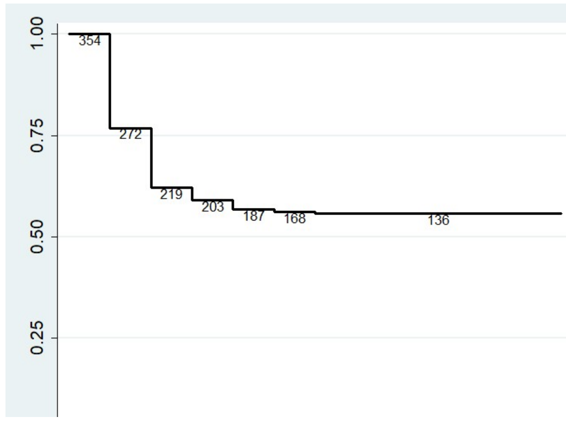

Figure 1. Kaplan-Meier survival estimate

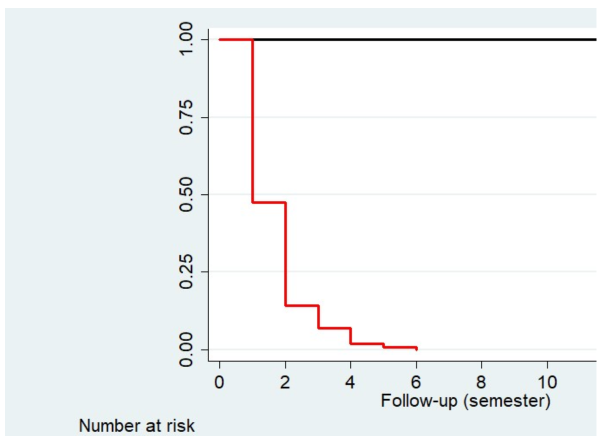

Figure 2. Kaplan-Meier curve based on active and non-active students

On univariate analysis, only one of the 5 variables tested had a p-value <0.25. There is no statistically significant difference in age, gender, employment status, and previous education level of students. However, based on the value of the crude hazard ratio (HR), students aged >45 y.o and 35-45 y.o have a risk of becoming non-active 1.2 times higher than students aged <35 y.o (Table 4). The tendency of older students to experience school dropouts is also found in previous studies (Carr, 2000; Saefuddin and Ratnaningsih, 2008). This is inversely proportional to other studies which suggest that older students in distance learning have a lower risk of dropping out of school (Ratnaningsih, 2011; Stoessel, Ihme, Barbarino, Maria-Luisa, & Sturmer, 2015). It is known that students at distance learning are not limited in age, year of entry, or year of graduation

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(Pannen, 2016), and generally students in distance learning are adults. The risk of male students being non-active is 1.08 times higher than females (Table 4). This result is also found in another study (Saefuddin & Ratnaningsih, 2008; Rumberger, 1983). The higher risk of dropping out in males is associated with lower learning resistance in males than in females. On the contrary, findings by Stoessel, Ihme, Barbarino, Maria-Luisa, & Sturmer (2015) showed the risk of dropping out female is greater than males, which can be contributed to the characteristics of distance learning students who generally are those who are already married (It can be associated with maternity, high household responsibilities, in-laws' restrictions, moving to a new city or other family obligations) (Carreira & Lopes, 2018; Muslim, Muhammad, Raza, & Touseef, 2017). Based on employment status, unemployed students have a risk of 1.2 times becoming non-active compared to those employed. Students who have bachelor's degrees have a risk of becoming non-active 5.8 times higher than students who have diploma degrees (Table 4). The findings related to sociodemographic characteristics can be used as a reference in an effort to decrease non-active students. It is necessary to optimize distance learning activities that put more attention to the learning characteristics of adults and emphasize more on students classified as male, unemployed, and bachelor's degree as previous education level.

As mentioned before, only one variable that had a p-value <0.25 and was included in the multivariate analysis, namely grade point average. In the final model, having GPA less than 2.00 (adjusted hazard ratio [aHR]: 2.39, 95% CI: 1.51–3.80) is the strongest predictor of the non-active student (Table 4). This finding is in line with previous studies which found students with lower GPAs had a higher risk of dropout than students who have higher GPAs (Saefuddin & Ratnaningsih, 2008; Ratnaningsih, 2011). The results of our study reveal that GPA is a good predictor to identify students who become non-active. A good GPA is an important point for students to survive studying at the Universitas Terbuka. For this reason, it is necessary to develop learning innovations at UT, one of which is by providing various learning services that match individual learning styles, abilities, and tastes that are tailored to the learning objectives of each course (Twigg, 2001). The results of this study are expected to provide benefits for making effective interventions.

Table 4. Univariate and multivariate analysis of student characteristics and non-active student

Variable	Univariate analysis		Multivariate analysis	
	HR (95% CI)	p-value	Adj. HR (95% CI)	p-value

Age (years old)		0.360		-
< 35	1.00		-	
35-45	1.19 (0.81-1.78)		-	
>45	1.21 (0.49-2.97)		-	
Gender		0.636		-
Female	1.00		-	
Male	1.08 (0.79-1.48)		-	
Employment		0.313		-
Employed	1.00		-	
Unemployed	1.18 (0.85-1.66)		-	
Previous education level		0.380		-
Diploma	1.00		-	
High School	2.04 (1.13-3.68)		-	
Bachelor	5.84 (2.04-16.68)		-	
Grade Point Average		<0.001		<0.001
>3.00 (0)	1.00		-	
2.00-3.00 (1)	6.02 (~)		6.02 (~)	
<2.00 (2)	2.39 (1.51-3.80)		2.39 1.51-3.80)	

4 CONCLUSION

The percentage of non-active students in the Biology Department is relatively high, with the incidence rate of non-active students being 8.7 per 100 people per semester. In one semester of observation, 75% of students become non-active. It means that the first semester is the best time to identify the student who is at risk become non-active. There is no statistically significant difference in age, gender, employment status, and previous education level of students. Grade Point Average (GPA) is the strongest predictor of the non-active student. Students with GPAs less than 2.00 had 2.4 times higher risk of being non-active students than those who have GPAs more than 3.00.

Efforts that need to be considered to reduce non-active students, especially in the first semester, are to improve the interaction between tutors and students through the provision of learning services that are preferred in the initial semester. The provision of these services needs to be

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supported by policies that can increase student involvement in these learning services, as well as maintain the quality of those services. In addition, optimizing learning activities must pay attention to students who have lower GPAs. The institution also needs to improve the socialization of the distance learning system so that students can prepare the best strategies for learning at the distance. Our research recommends strengthening student GPA monitoring throughout the first semester, and it will improve the prediction accuracy of non-active students. It also can be the key to success in reducing the number of non-active students in distance learning. Further research is suggested, e.g. by analyzing other variables to find other predictors that can be used to identify non-active students (student dropout) in distance learning.

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