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AUTOMATED TELLER MACHINE (ATM) DURABILITY ANALYSIS USING SURVIVAL ANALYSIS (EVIDENCE BASE IN INDONESIA)

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Abstrak

Salah satu cara meningkatkan kepercayaan nasabah yang juga merupakan salah satu keunggulan kompetitif bank adalah kualitas layanan Anjungan Tunai Mandiri (ATM). ATM juga memegang peranan penting terhadap kinerja bank karena ATM memberikan pengaruh yang positif pada kinerja bank sehingga pemeliharaan ATM, menjadi penting bagi bank. Pemeliharaan yang proaktif pada ATM sebelum terjadi kerusakan, juga akan berdampak pada peningkatkan kualitas layanannya. Oleh karena itu, penting bagi bank untuk dapat mengetahui estimasi kapan terjadi kerusakan pada ATM. Penelitian ini bertujuan untuk menganalisis waktu sampai terjadinya kerusakan (*time-to-event*) pada ATM dan karakteristik penentu yang dapat mempengaruhi ketahanan ATM dengan menggunakan pendekatan analisis survival. Metode yang digunakan adalah Analisis *Survival Nonparametric Model, Kaplan Meier*, dan Analisis *Survival Nonparametric Model*, *Cox Proportional Hazard (Cox PH)* pada 11.043 data ATM tahun 2019-2023 pada salah satu bank terbesar di Indonesia. Hasil analisis Kaplan-Meier, menunjukkan bahwa tidak terdapat perbedaan yang signifikan pada ketahanan ATM antar kelompok pada lokasi, merek, dan pengelola. Dari analisis *Cox PH*, ditemukan bahwa faktor-faktor yang mempengaruhi dan signifikan adalah jenis, durasi penyimpanan mesin setelah dilakukan pembelian sebelum dilakukan aktivasi, merek, dan frekuensi transaksi ATM. Sedangkan frekuensi kegiatan *Corrective Maintenance* (CM) berpengaruh namun tidak signifikan pada ketahanan ATM. Analisis ketahanan ATM ini dapat digunakan sebagai dasar pengambilan keputusan tentang karakteristik ATM yang akan digunakan, sehingga bank dapat meningkatkan kualitas layanan ATM dan mempertahankan keunggulan kompetitifnya.
Kata kunci : Anjungan Tunai Mandiri (ATM), Analisis Survival, *Cox Proportional Hazard, Extended Cox, Time-To-Event*

Abstract

One way to increase customer trust, which is also one of the bank's competitive advantages, is the quality of Automated Teller Machine (ATM) services. ATM also play an important role in bank's performance because ATM have a positive impact on bank's performance, so that ATM maintenance is important for bank. Proactive maintenance of ATM before failure occurs will also have impact on improving ATM service quality. Therefore, it is important for banks to be able to know the estimation of when failure occurs. This study aims to analyze the time-to-event of ATM and the determining characteristics that can affect ATM durability using survival analysis approach. The methods used are Nonparametric Survival Analysis Model, Kaplan Meier, and Nonparametric Survival Analysis Model, Cox Proportional Hazard (Cox PH) on 11,043 ATM data for 2019-2023 at one of the largest banks in Indonesia.The results of the Kaplan-Mayer analysis, there is no significant difference in survival probability ATM between groups on variable location, brand, and operation management. From Cox PH analysis, it was found that the influencing and significant factors are type, duration of machine storage after purchase before activation, brand, and frequency of ATM transactions. While the frequency of Corrective Maintenance (CM) activities has an effect but not significant on ATM durability. This ATM durability analysis can be used as a basis for decisions about the characteristics of ATM that are implemented, so that banks can improve the quality of ATM services and maintain their competitive advantage.
Keywords: *Automated Teller Machine (ATM), Survival Analysis, Cox Proportional Hazard, Extended Cox, Time-To-Event*

INTRODUCTION

Indonesia is very open to digital banking (McKinsey&Company, 2019), but customers still prefer the use of Automated Teller Machine (ATM) over other electronic media or financial services. Through the McKinsey Asia PFS survey (2017), showed that access to financial services through conventional branches and ATM in Indonesia is still relevant. Four (4) out of five (5) respondents mentioned that the location of branches and ATM from banks is the reason respondents choose banks. The importance of ATM for banking customers, especially in Indonesia, is shown through the results of the survey that shown in the Digital Literacy Status in Indonesia 2021 , the digitalization and the Internet of Things (IOT), does not make the popularity of ATM disappear, as seen from 73.5% of respondents still access banking services by ATM, compared to electronic money 2.2%, mobile banking 13.3%, and Internet banking 7.7%.

The importance of ATM as a media to access financial transactions for customers, and for banks, as a media for reaching and providing banking services for customers, has been discussed and shown in previous research. (Ayuningtyas and Sufina, 2023) Automated Teller Machine (ATM) becomes the competitive advantage for bank, and (Mitha Christina Ginting et al., 2021) have a positive impact on bank performance, because the distribution of ATM is currently spread in various locations and easy to access and use. The study on the effect of mobile banking, agency banking, ATM banking and online banking on the financial performance of commercial banks listed in Kenya concluded that any increase in ATM units would lead to an increase in the financial performance of commercial banks listed on The Nairobi Securities Exchange (NSE) (Mary and Isola, 2019). The study also concluded that ATM banking strongly and positively affects the financial performance of commercial banks listed in Kenya. So it is understandable if banks in Indonesia still maintain their ATM networks. In fact, the leader in the banking industry in Indonesia, still retains the population of its ATM network.

Increasing the services of ATM, ATM must operate longer (always on). The longer and the better the durability of the machine, the more customers can be served, and more transactions can be processed. The Banks have to be able to maintain the ATM service quality, that customers can access at ATM and the availability of ATM continuously, without errors, and provide services for customers (Nigatu et al., 2023). Maintaining ATM availability, maintenance is necessary.

Maintenance is a combination of technical and administrative activities to maintain or restore a unit to a state where the unit can work in accordance with the expected function (Ben-Daya et al., 2016). (McKinsey, 2018) predicts that improvements and reliability of digital transformation, can increase the availability of assets from 5% to 15%, and can reduce maintenance costs 18% - 25%. Proper maintenance can help avoid unexpected failure, reduce the time the machine is unable to provide services or is not operating (downtime), so that it can provide profits for banks and also increase customer satisfaction, Faster Capital (2024).

The development or transformation of industrial technology 4.0, Big Data and the Internet of Things (IoT) drives the development of the maintenance concept of Marek (Molęda et al., 2023), and a more proactive maintenance process becomes more popular, Predictive Maintenance (PdM). PdM, is maintenance when it is needed, or just before a failure occurs, (Molęda et al., 2023). (Korvesis, 2019), using Machine Learning (ML), a time series method to describe the time until failure in aviation, which utilizes event-log data, sensors, and logbook/maintenance history to predict the future failure. Using the history of event-log, and the classic ML, the binary classification method, Random Forest (RF), (J. Wang et.al, 2017) can predict the ATM failure time.

Research was done on 1557 Wincor ATM that were online in North America. The research has shown that PdM on ATM, can determine parameters flexibly using machine learning. The main PdM approach is to predict unit failure. Predictive Maintenance (PdM) is one way to apply Survival analysis, because it can provide information about the time when failure occurs in a unit, before providing information to related parties to carry out maintenance.

Survival analysis is a statistical science that provides an overview of the time-to-event/time- to-failure and the variables that influence the survival time (Kleinbaum and Klein, 2012), shown in figure 1. Survival analysis provides a broader analysis of the probability of survival, through survival curve, the factors that affect survival time, and how much these factors affect the survival time, as well as the hazard ratio between each factor.

Figure 1. Time-To-Event (Kleinbaum dan Klein, 2012)

The use of Survival Analysis is widely used in the health or medicine world. (Hui P Zhu et al, 2011) performed Parametric-Survival Analysis, for 1715 patients with stomach cancer to find out the factors that can describe the survival time, such as age, gender, stage of cancer and others and compare the best models between the Weibull model or Cox model. Thus shown that the Weibull model can elicit more precise results as an alternative to Cox. The research of 30 patients with acute myeloid leukemia (AML) (Angela, 2011), used and compared Weibull and Cox Proportional Hazard (Cox PH) in determining the best model to model the survival rate, which resulted in that if the data distribution is known, the Weibull model is better, but if the shape of the data distribution cannot be known, the Cox Proportional Hazard model is a good alternative. However, the use of the Cox PH model must be followed by the proportional hazard assumption, where the between-group hazard ratio of a single covariate is constant over time. If this assumption is not met, it can be addressed with an extended Cox model that shown in the research the recurrence of cervical cancer patients (Adharina & Purnami, 2017), found that modeling the recurrence of cervical cancer patients can also be done with survival analysis, to address the proportional hazard assumption that was not met by covariates, Cox Extended regression was used, with a time function, $g(t) = ln(t)$, with the smallest AIC value.

The use of Survival analysis is not only widely used in the health or medicine world, but also in manufacturing. (Hrnjica, and Softic, 2021) performed research of small dataset, 100 turbofan engines using the most popular Kaplan-Mayer (KM) model, a non-parametric approach and Cox proportional hazard (Cox PH) semi-parametric approach. Kaplan–Mayer model was used to give an overview of the survival curve, while Cox PH was to find out the covariates that influenced the durability of the engines. (Orumie and Nvene, 2018), discovered, using Weibull Survival Analysis, that an ATM can perform 74 transactions and operate for 236.51 minutes, before eventually failing or having damage. (Oramie and Nvene, 2018) conducted research on sample 20 ATM transactions, but attempts to determine the durability of the ATM were not accompanied by the search for factors that influenced the stability of those ATM.

This research aims to provide a more comprehensive and broad analysis of the Survival analysis on the durability of ATM, by providing an overview of the survival curve of the ATM using the non-parametric, Kaplan-Mayer (KM) approach and finding the covariates that contributes to the engine's durability, using the Cox proportional hazard method (Cox PH) semi-parametric approach, and to predict the best model for its hazard function. By collecting a lot of data, population ATM data from one of the largest bank with the widest ATM network in Indonesia and a long duration of research (5 (five) years) can make a good contribution to the level of accuracy and the variation of data. The research could also contribute to the Indonesian banking industry, especially banks with a large ATM network, to gain new perspectives in determining the characteristics of machines that will be purchased, placed in the future, and things that affect the durability of ATM, as well as changes in maintenance mechanisms to improve the competitive advantage of companies.

SURVIVAL ANALYSIS

Survival analysis is analysis of survival time and factors that influence that survival time (Dirk F. Moore, 2016) which is also a sub-science of statistics, (Kleinbaum and Klein, 2012), which is a set of statistical procedures to find out time-to-event until an event occurs. The Response Variable in survival analysis is the time until an event occurs (Figure 1). An event can be anything, death, failure of machine, illness, and etc. Time is a survival time. The key characteristic of SA is a positive response variable (a non-negative discrete or continuous random variable). In this case, the time from the beginning of observation, until the event occurs, must be well defined.

Generally, the probability survival time until time (t) defined as F_x, where:

$$F(t) = Pr[T_x \leq t], \quad (1)$$

Then, the survival function S(t) is defined as the probability for survival after time t of the random variable T,

$$S(t) = 1 - F(t) = Pr[T_x > t], \quad (2)$$

In SA, there is also the Hazard Function, which can be defined as the instantaneous potential for an event to occur, given a very small amount of time (Kleinbaum and Klein, 2012).

$$h_t = \frac{f(t)}{S(t)} = \frac{-S\prime(t)}{S(t)}, h_t = -\frac{d}{dt} \log S(t) \quad (3)$$

(P. Wang et al., 2017), Survival analysis, can be divided into 2 (two) general categories, Classical Statistical Methods, and Machine Learning Methods. (ML). Both methods have the same purpose of predicting survival time. ML is used for high-dimensional data, whereas Classical statistical methods are used for lower dimensional data. Traver Hastie et al. (2015), high-dimensional data is data with more variables than the number of samples. Based on the assumptions and how the parameters are used in the model, the classical statistical methods can be divided into three categories, (i) non-parametric model, (ii) semiparametric model, and (iii) parametric model. The method of Survival analysis can be shown as follows:

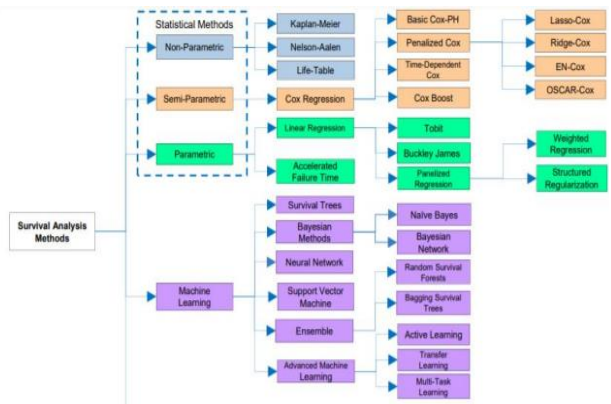

Figure 2. Survival Analysis Method (P. Wang et al., 2017)

To be able to define accurately, the second characteristic of SA is censoring. Censoring happens, because of several things, (a) an observation unit or a person does not experience the specified event (failure) until the end of the observation time is completed and (b) an observation unit or a person cannot be observed (lost to follow-up) during the study period. Example: a person died during the study period, while death because of car accident, which was not an event, but the observed event was a heart failure.

METHODS

Data Preparation

This study conducted ATM data sets from one of the largest bank that also one of the banks that have the widest ATM network in Indonesia. The dataset is ATM data activated during the observation period of January 1, 2019 - December 31, 2023. In this case, the ATM used are ATM that have not been activated or repaired before.

The event in this study is hardware failure that causes hardware replacement for the first time since activation and the time-to-event will be considered as the form of time in days. There are factors that considered for this research

a) ATM Type, X_1_Type, 0 for Multi Function (MF), the ATM can be used for withdrawal and non-cash transactions and 1 for Cash Recycling Machine (CRM), the ATM can be used for cash (deposit and withdrawal) and non-cash transactions
b) ATM Location, $X_2\_Location$, 0 for Public Area and 1 for Bank's Branch
c) ATM Storage Duration, $X_3\_Duration$, 0 for Short and 1 for Long
d) ATM Merk, X_4_Merk, 0 for Others, and 1 for merk HT
e) ATM Average Transaction per Day, $X_5\_Transaction$, numeric variable
f) ATM Operation Management, X_6, Third Party, Internal Staff
g) ATM Corrective Maintenance Frequency, X_7, numeric variable.

Hypotheses

There are several hypotheses that address the relationship between ATM characteristics and the ATM durability:

a) H_0= There is no difference between the type of ATM, CRM and MF, on ATM durability

H_1= There is a difference in influence between ATM types, on ATM durability, where CRM has a negative influence on ATM durability

b) H_0= There is no difference between the location of ATM placement, branches and other public area on ATM durability

H_1= There is a difference in influence between the location of ATM placement, on ATM durability, where branch location has a negative influence on ATM durability

c) H_0= There is no difference between the duration of ATM storage, either long or short, on ATM durability

H_1= There is a difference between the duration of ATM storage, whether long or short, on ATM durability, where long duration has a positive effect on ATM durability

d) H_0= There is no difference between ATM merk, on ATM durability

H_1= There is a difference between ATM merk, on ATM durability, where ATM merk, HT have a negative influence on ATM durability

e) H_0= There is no difference the number of machine transaction frequencies, on ATM durability

H_1= There is a difference of the number of machine transaction frequencies, on ATM durability, where the addition of transaction frequency has a positive effect on ATM durability

f) H_0= There is no difference in the influence between ATM Operation management, Third Party or Internal Staff, on ATM durability

H_1= There is a difference between ATM Operation management, on ATM durability, where machines managed by Third Party have a positive effect on ATM durability

g) H_0= There is no difference in of the number of Corrective Maintenance (CM) frequencies, on ATM durability

H_1= There is a difference of the number of Corrective Maintenance (CM) frequencies, on ATM durability, where the addition of Corrective Maintenance (CM) frequency has a negative influence on ATM machine durability.

Non Parametric Model, Kaplan-Mayer (KM) Model

(Kaplan-Mayer, 1958) developed the Kaplan-Mayer (KM) Curve to provide estimates of survival functions with real time intervals. The estimator of the survival function (including censored observational data) can provide the probability that a unit of observation will survive beyond a certain time which can be calculated through the formula,

$$S(t) = \Pi_{t_s \le t}\left(1 - \frac{d_j}{n_j}\right) \quad (4)$$

Where, $for\ t = 0, S(t) = 1$ and
$for\ t = \infty, S(t) = S(\infty) = 0$

Semi Parametric Model, Cox Proportional Hazard (Cox PH)

Cox Proportional Hazard (Cox PH) is a Semi-Parametric method which is also an extension of the Non-Parametric Kaplan-Mayer (KM) method. The Cox PH method was developed to see the relationship between predictive variables (explanatory variables) with survival time / time-to-event through the hazard function.

$$h(t) = \frac{f(t)}{S(t)} \quad (5)$$

for one covariate, the hazard function shown,

$$h_x(t) = h_0(t)exp(\beta(x)) \quad (6)$$

But for multivariate, the hazard function shown,

$$h_x(t) = h_0(t)exp(\beta_1(x_1) + \beta_2(x_2) + \beta_3(x_3) \quad (7)$$

Where, $(x_1, x_2, x_{3,} \dots, x_n)$ are the variable, and $(\beta_1, \beta_2, \beta_3, \dots \beta_n)$ are the regression coefficients for each variable.

The Hazard Ratio (HR) can be defined as the hazard for an individual divided with the hazard for another individual, that attach to the same factor, variable

$$\frac{h(t,X_i^*)}{h(t,X_i)} = \frac{h_0(t)exp(X_i^*\beta)}{h_0(t)exp(X_i\beta)} = exp[(X_i^* - X_i)\beta] \quad (8)$$

(Kleinbaum and Klein, 2012), for the Cox Proportional Hazard (Cox PH) model, the proportional hazard assumption that must be attained. One way that can be used is to test the proportional hazard assumption through the Goodness of Fit approach, Schoenfeld residuals. Testing the correlation between Schoenfeld residuals and rank survival time. Checking the proportional hazard assumption is the p-value and (rho) value.

The hypothesis used in this correlation test is as follows,
H_0: ρ = 0 (PH Assumption is attained, Variable is time - Independent)
H_1 : ρ ≠ 0 (PH Assumption is not attained, Variable is time -Dependent)

RESULTS AND DISCUSSION

Kaplan-Mayer (KM) Model

The analysis conducted in this study, using Survival Analysis-Non Parametric, Kaplan-Mayer (KM), which can provide an overview of the distribution of the chances an ATM machine can survive until a certain time. The data obtained is processed with R Studio Software. With the Kaplan-Mayer method, for the entire ATM durability data, it is found that the ATM durability data has a median of 318 days which is presented in Table 1. It can also be seen that in Figure 3, the time for the event to occur for the first time is 8 (eight) days. The greater the time value, the smaller the chance to survive. After the eighth time, it can be seen that every day an event occurs. This shows that ATM is very vulnerable to events.

Table 1. Kaplan-Meier Survival Function Estimation Results Without Variables

N Risk	*Event*	Median
11043	7231	318

Kaplan-Mayer, can provide information on differences in survival curves between groups for each covariate.

a) The survival curve for the CRM type is better when compared to the survival curve of the MF type which is below the CRM survival curve with the median of, CRM is 322, while the median of the ATM, MF type, is 300. This shows that in general the CRM type has better survival than MF. To determine if there is a significant difference in survival between the ATM, MF and CRM types, a non-parametric Log-Rank statistical test was performed, with a p-value (p) = 2e-07, which is < α = 0.01, thus rejecting H_0, it can be concluded that there is a significant mean difference in survival between the ATM, MF and CRM types.

b) The survival curves for both ATM machine placement locations do not have a clear difference, with the median of the ATM machine placement locations in branches and shops being the same, namely 318. From the non-parametric Log-Rank statistical test, with the result of p-value (p) = 0.55, which is > α = 0.01, thus failing to reject H_0, it can be concluded that there is no significant mean difference in survival between ATM placement locations.

c) The curve shows that the durability of ATM stored longer in the warehouse is lower than those stored with short or long duration, with a median, long duration location of 298 compared to short duration of 327. From the non-parametric Log-Rank statistical test, with the result of p-value (p) = 5e-11, which is < α = 0.01, thus rejecting H_0, it can be concluded that there is a significant mean difference in durability between new and old ATM storage categories.

d) The survival curve is based on the ATM merk, which has only a slight difference between the "HT" brand, and other brands. with the median between the "HT" brand and others differing by 313, for the "HT" brand and 322 for other brands. With the non-parametric Log-Rank statistical test, the p-value (p) = 0.77, which is > α = 0.01, thus failing to reject H_0, it can be concluded that there is no significant mean difference in survival between the "HT" brand and others.

e) From the curve, we cannot clearly see the difference between the durability of ATM machines managed by branches and third parties (PKT), although the median durability of ATM machines managed by BCA internally, i.e. branches, is greater, 326, compared to the median managed by third parties, i.e. 317. With the non-parametric Log-Rank statistical test, the p-value (p) = 0.24, which is > α = 0.01, thus failing to reject H_0, it can be concluded that there is no significant mean difference in durability between managers.

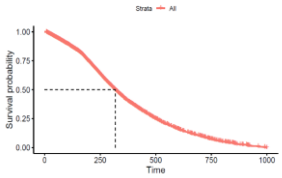

Figure 3. Survival Curve with Kaplan-Meier Model

Source : ATM Data Processed by R.Studio

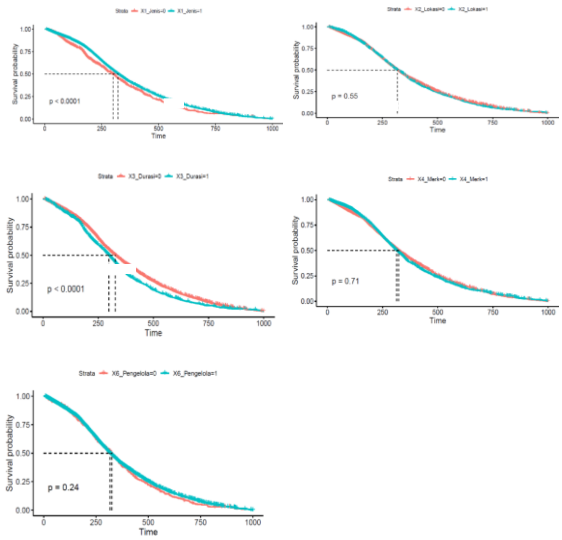

Figure 4. Survival Curve with Kaplan-Meier Model For Categorical Variables

Source : ATM Data Processed by R.Studio

Cox Proportional Hazard Model (Cox PH)

Finding out how 7 (seven) covariates/variables affect ATM durability, a semi-parametric analysis will be conducted, namely Cox Proportional Hazard (Cox PH). However, in CoxPH analysis, it is necessary to test for proportional hazard, where the hazard ratio of each covariate is constant over time. If the proportional hazard assumption cannot be met, an extended Cox analysis will be conducted. Before testing the proportional hazard assumption, first find the Cox regression model, taking into account the Wald test value and p-value either partially or simultaneously on all covariates, to determine whether the covariates jointly or partially have a significant effect on ATM resistance. the general form of Cox PH containing all the covariates tested.

$$h(t,X) = h_0(t)exp[-0.24490X_1 + 0.27160X_2 + 0.13770X_3 - 0.19080X_4 + 0.00248X_5 - 0.02514X_6 - 0.1268X_7\,] \quad (9)$$

Table 2. Regresi Cox For All Covariates

Covariates	*Coef*	*Exp(coef)*	*Pr*(> |*z*|)	*Significant*
X1_Type	-0.24490	0.78280	0.0000000000419 ***	*Significant*
X2_Location	0.27160	1.31200	<2e-16 ***	Not Significant
X3_Duration	0.13770	1.14800	0.00000766 ***	*Significant*
X4_Merk	-0.19080	0.82630	0.000000000146 ***	*Significant*
X5_Transaction	0.00248	1.00200	<2e-16 ***	*Significant*
X6_Management	-0.02514	0.97520	0.667	Not Significant
X7_FreqCM	-0.12680	0.88090	<2e-16 ***	*Significant*

*Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

To determine the significance of the model simultaneously on ATM durability, a parameter test is conducted, which shows the p-value of the likelihood ratio test with a p-value of < 2e-16, which is < α = 0.01, resulting in a decision to reject H_0, that there is at least one independent variable that has a significant effect on the model. So it can be concluded, the Cox model in general that is formed together has a significant effect on ATM durability. For partial test, the variables that are not significant are X2_Location and X6_Management. Because of this, backward elimination is carried out, using the backward step iteration in the R Studio software, to determine the best Cox proportional hazard model. Furthermore, the best Cox regression model will be selected by choosing the model with the smallest Akaike's Information Criterion (AIC) value.

With the smallest AIC value generated through backward selection, the best model is obtained.

$$h(t,X) = h_0(t)exp[-0.2452X_1 + 0.2757X_2 + 0.137X_3 - 0.1901X_4 + 0.00248X_5 - 0.127X_7\,] \quad (10)$$

Table 3. The Best Regresi Cox Model

Covariates	*Coef*	*Exp(coef)*	*Pr*(> |*z*|)	*Significant*
X1_Type	-0.24520	0.78260	0.0000000000394 ***	*Significant*
X2_Location	0.27570	1.31700	<2e-16 ***	Not Significant
X3_Duration	0.13700	1.14700	0.00000824 ***	*Significant*
X4_Merk	-0.19010	0.82690	0.000000000159 ***	*Significant*
X5_Transaction	0.00248	1.00200	<2e-16 ***	*Significant*
X7_FreqCM	-0.12700	0.88070	<2e-16 ***	*Significant*

*Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

The simultaneous significance test of the model obtained the p-value of the likelihood ratio test with a p-value of < 2e-16, which is < α = 0.01, resulting in a decision to reject H_0, that there is at least one independent variable that has a significant effect on the model. In addition to conducting simultaneous tests, partial tests were also carried out on each covariate in the model. X2_Location is not significant.

Cox proportional Hazards Assumption Test

Furthermore, after obtaining the best Cox regression model, will be tested for the proportional hazard assumption, using the Goodness of Fit (GoF) test, the correlation between the Schoenfeld residual and the rank of survival time, which can be seen from the p-value and the rcount (rho) value. The results of the test shows, the variable with p-value < α = 0.01, namely X7_FrekCM, thus failing to reject H_0, which indicates that the X7_FreqCM* variable does not meet the proportional hazard assumption, so that it will then be overcome using the extended Cox model.

Tabel 4. Uji *Goodness of Fit* (GoF)

Covariates	chisq	df	*p-value*
X1_Type	5.256	1	0.022
X2_Location	1.727	1	0.189
X3_Duration	3.107	1	0.078
X4_Merk	0.492	1	0.483
X5_Transaction	1.518	1	0.218
X7_FreqCM*	63.274	1	1.80E-15
GLOBAL	72.421	6	1.30E-13

Cox Extended Model

1. Extended Cox regression model with $g_1(t) = t$

Parameter estimation by the extended Cox regression model with $g_1(t) = t$, by multiplying the variable that does not meet the proportional hazard assumption, X7_FreqCM* with $g_1(t) = t$. Then the multiplication will produce a variable, X7_FreqCM_t, with the Extended Cox regression results which can be seen in Table 4. which has AIC value, 111,588.5

Tabel 5. Regresi *Extended Cox Model* With $g_1(t) = t$

Covariates	*Coef*	*Exp(coef)*	$Pr(>\|z\|)$	*Significant*
X1_Type	-0.33390	0.71610	<2e-16 ***	*Significant*
X2_Location	0.06027	1.06200	0.05205.	Not Significant
X3_Duration	0.08583	1.09000	0.00507**	*Significant*
X4_Merk	-0.16480	0.84810	0.000000036***	*Significant*
X5_Transaction	0.00203	1.00200	<2e-16 ***	*Significant*
X7_FreqCM	0.61670	1.85300	<2e-16 ***	Not Significant
X7_FreqCM_t	-0.00159	0.99840	<2e-16 ***	*Significant*

*Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

2. Extended Cox regression model with $g_1(t) = log\ t$

Parameter estimation by the extended Cox regression model with $g_2(t) = log\ t$, by multiplying the variable that does not meet the proportional hazard assumption, X7_FreqCM* with $g_2(t) = log\ t$. Then the multiplication will produce a variable, X7_FreqCM_logt, with the Extended Cox regression results which can be seen in Table 5. which has AIC value, 110,464.1

Tabel 6. Model Regresi *Extended Cox* dengan fungsi $g_2(t) = log.t$

Covariates	*Coef*	*Exp(coef)*	$Pr(>\|z\|)$	*Significant*
X1_Jenis	-0.29710	0.74300	0.000000000000000153***	*Significant*
X2_Lokasi	0.08747	1.09100	0.00423**	Not Significant
X3_Durasi	0.13140	1.14000	0.0000195***	*Significant*
X4_Merk	-0.18690	0.82960	0.000000000384***	*Significant*
X5_Transaksi	0.00191	1.00200	<2e-16 ***	*Significant*
X7_FreqCM	3.07500	21.64000	<2e-16 ***	Not Significant
X7_FreqCM_logt	-1.21900	0.29540	<2e-16 ***	*Significant*

*Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

Looking at the AIC value of the extended Cox model, $g_1(t) = t$ and $g_2(t) = log\ t$, the extended Cox model with the function $g_2(t) = log\ t$ which has the smallest AIC value, 110,464.1, is the best model, so that the hazard function can be shown as,

$$h(t, X) = h_0(t)exp[-0.2971X_1 + 0.087472X_2 + 0.1314X_3 - 0.1869X_4 + 0.00191X_5 + 3.075X_7 - 1.219X_7g_2(t)] \quad (11)$$

CONCLUSIONS

The Kaplan-Meier non-parametric analysis, it was found that ATM had an event, which is the first damage since it was activated on the 8th day, where almost every day there is a machine that experiences an event and has a median value of 318, which indicates that ATMs are electronic goods that are vulnerable to failure. The significant difference in survival curve between groups from each covariate, occurs between groups are categorical variables of type, and length of machine storage, while the variables of location, merk, and operation management of ATM, do not have significant difference in the survival curve.

From the Cox Proportional Hazard (Cox PH) analysis that can estimate the effect of ATM characteristics on the occurrence of events. With backward selection, it is found that the variables that have effect and significance with the occurrence of events in ATM are X1_Type, X3_Duration, X4_Merk, X5_Transaction and X7_FrekCM. However, after Goodness of Fit (GoF) testing, to see the fulfillment of the proportional hazard assumption, it is found that X7_FrekCM, does not meet the proportional hazard assumption, with a p-value < α = 0.01. So it will be solved with the extended Cox model.

The extended Cox model is one way that is used to address variables in the Cox model that do not meet the proportional hazard assumption, by interacting these variables with time. After the extended cox analysis, with $g_1(t) = t$ and $g_2(t) = log\ t$. The extended cox model with $g_2(t) = log\ t$ is the model with the smallest AIC, so that, the extended cox with $g_2(t) = log\ t$ is the best model to see the interaction of ATM characteristics with ATM time-to-event. Through partial testing, with a significance level of p-value < α = 0.01, it was found that the characteristics that have a significant effect on ATM durability are X1_Type, which has a negative value, where the type of ATM, CRM has a smaller risk when compared to MF. X3_Duration, which has a positive value, where ATMs, which are stored longer after purchase until activation have a greater risk of experiencing an instantaneous event when compared to those stored for a shorter period of time. X4_Merk, which has a negative value, where the ATM, HT brand has a smaller risk when compared to other brands. X5_Transaction, which has a positive value, where the addition of 1 (one) ATM transaction will have a greater risk of experiencing a part change for the first time since activation. X7_FrekCM, which has a positive value, where every occurrence of damage that requires Corrective Maintenance (CM) action on the ATM will have a greater risk than those that do not.

This ATM resilience research is only conducted with data sourced from one bank in Indonesia, which cannot represent ATM resilience analysis in general either in Indonesia or in other countries. It is still necessary to conduct research on other machine characteristics, such as temperature, customer behavior when using ATM machines, regional clusterization, and hardware specifications, as well as machine error-logs that may have different influences on ATM durability. This research is also limited using survival analysis, non-parametric, and semi-parametric methods only, and has not seen the suitability of ATM resilience to certain distributions, and estimation of resilience using machine learning yet. So for these limitations, future research is recommended to analyze the durability of ATM machines, with data from various companies or even countries, and add temperature characteristics to covariates, as well as try clustering data or using parametric, or machine learning survival analysis methods.

SUGGESTIONS

Although this research has been successful in providing estimates of time-to-event and the effect of ATM characteristics on ATM resilience, it is important to note that it still has various limitations that can be used as developments in future research. These include:

1. This study is only based on ATM data at one bank in Indonesia, which may not represent ATM resilience analysis in general, either in Indonesia or in other countries.
2. Further research is required on other machine characteristics, including temperature, customer behaviour when using ATM machines, regional clusterisation, and hardware specifications. Additionally, machine error logs may have a different effect on ATM resilience.
3. Furthermore, this research is limited to using survival, non-parametric, and semi-parametric analysis methods, which has not allowed for an assessment of the suitability of ATM resilience to certain distributions and estimation accuracy using machine learning.

In light of these limitations, it is recommended that future research should test the durability of ATM machines with more data from various companies or even countries. Furthermore, temperature characteristics should be added to covariates and clustering data, or parametric survival analysis methods or machine learning should be used.

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