ANALYSIS THE EFFECT OF SERVICE REQUEST HANDLING ON THE OCCURANCE OF SYSTEM DISRUPTION IN ABC TELCO COMPANY

Erwin Hidayat[1], Gadang Ramantoko[2]

[1-2] School of Economics & Business, Telkom University, INDONESIA.

[1]erwinh.zidane@gmail.com, [2]gadangramantoko@gmail.com

ABSTRACT

ABC Telco Company has made the IT (Information Technology) unit as the spearhead in winning competitions in the Cellular Telecommunications world. Almost no business in this world can succeed without technology support. Today's IT unit is no longer a support function, but has evolved into a business service. The role of Information Technology must be able to ensure all entities in the company to obtain the necessary, quality, valid, fast and safe information. Therefore, the IT unit at ABC Telco Company implements the ITIL (Information Technology Infrastructure Library) framework as an International standard in managing Information Technology services recognized in the world so that IT services can provide quality services and information for all business users and management in decision making, so that ABC Telco Company remains the champion.

The focus of this study is on the Service Request Management (SRM) function, which is a small part of ITIL, which is a medium for business users to request services from IT Service Management units (ITSM) in solving problems that occur in their respective functions in a direct and good relation or indirectly in serving customers of ABC Telco Company. Analysis of the data contained in this SRM is very important, so that IT ABC Telco Company gets a more accurate picture of the relationship of certain variables to system disruption groups, to be used as input to prepare preventive measures so that system disruptions that will occur can be minimized because they can be mapped and predicted, and can be used to reclassify parameters. in SRM so that the handling process for system disruption is happening, more effective and efficient. This study analyzes data service requests from January 2018 to Jun 2018, using the R application and probability analysis with Orange software version 3.8.

Keywords: ITIL, Service Request, System Disruption, ITSM, Probability Analysis.

INTRODUCTION

Background

Information technology contributes to increasing effectiveness and efficiency and in delivering business strategies to the company's operations. Increased investment in the implementation of technology shows that information technology has a performance that is in line with the achievement of the company's business strategy (ITIL | Information Technology Infrastructure Library, 2017). The implementation of information technology in companies sometimes has obstacles in its application so that the benefits of implementing information technology cannot be fully felt. Factors that influence the inhibition of information technology implementation include limited number of IT employees, limited ability of IT employees, low level of information technology security, low level of sustainability of information technology, and low management level of information technology service operations (IT GEIT Global Status Report, 2011).

Copyright © 2019

In the work Operation Management book (Heizer, 2006) it is stated that in order to achieve Competitive advantage through operations management, there are 3 approaches that can be taken, There are Differentiation to get better results, Cost Efficiency, and Improve response to get faster dan more effective results.

From the data regarding the number of job programs in the system that are increasing (around 3% per month) and the number of system disruptions that tend to increase (around 8% per month), the researchers need to conduct research for the effect of handling service request processes on the occurance of system disruptions, since IT Service Management requires to improve time efficiency, minimize human error, provide excellent quality processes, minimize the number of incident systems that occur.

Human error is failure to carry out certain tasks that can cause disruption of scheduled operations or cause damage to equipment and property. The performance target results are achieved through the behavior of people who do their jobs. If behavior does not reach the desired goal, it is called human error (Dhillon, 1986).

Human error occurs because human behavior can be wrong and can be caused by lack of concentration, unmotivated, ergonomic factors and various psychological and physical factors. It is possible to overcome these factors in an effort to improve human performance (Reason, 1990).

OBJECTIVES

Some of variables related to possibility of human error on the occurance of system disruption are going to be measured and analyzed to get answer of the following question:

a. Is the service categorization affect significantly to the system disruption?
b. Is the symptom group affect significantly to the system disruption?
c. Which are the type of system disruption that can be predicted very well or not as well as what the predictive value is ?

METHODOLOGY

Population and Sample

According to the type of research and data analysis, this research categorized as quantitative. Quantitative research methods are research methods that try to make accurate measurements of behavior, knowledge, or opinion (Indrawati, 2015).

In this research, the population is all data in the service request management system that establish in the ABC Telco Company since 2012 with the total population are around 180.000. Population data on the service request management system is homogeneous, all data are kind on daily basis, so within random sampling method (Slovin formulas), sampling data taken over a period of 6 months during January 2018 to Juni 2018 amounting to 13.162 data, could represent each member of population, and has met with the requirement criteria.

Research Stages

The research was conducted through several stages as visualized in figure 1 :

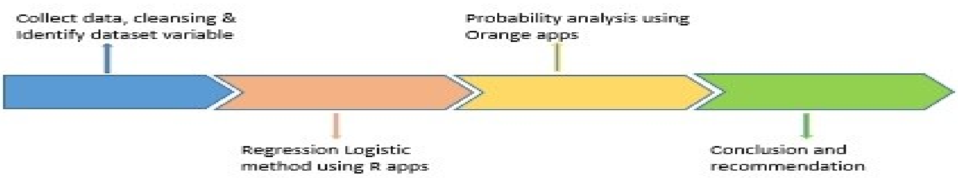

Figure 1. Research Stages

Operational Variables

The independent variables chosen by the researcher are variables related to the possibility caused by human error, since human error has a role around 80% to 90% in determining the occurance of system disruption (Primadewi, Widjasena, Wahyuni, 2014). There are 2 (two) variables that identified as independent variables consist of service categorization and symptom group. The form of the relationship between independent variables and dependent variables in the form of correlational relationship and causal relationship. In accordance with social phenomena, the form of the relationship between predictor variables and response variables can be positive and negative, can be influential or not influential (Sudiro, 2012). Therefore, the researcher suspects that some of variables in the data set are the causes of system disruption as dependent variable.

There are several type of system disruption as visualized in the table 1:

Table 1. Type of System Disruption

No.	Code	Type of System Disruption
1	A	Custom Reporting Problem
2	B	Activation Error Problem
3	C	Card or Voucher Invalid
4	D	Wrong Billing Statement
5	E	Payment System Problem
6	F	Electronic Money System Problem
7	G	Job schedulling Problem
8	H	User Access Problem
9	I	Active Period Extension Problem
10	J	USSD System Problem
11	K	Block Unblock System Problem
12	L	Loyalty System Problem

Data Processing

At this stage, the researcher conducted data cleansing by removing the special characters an all existing data. This activity to be done, so the data to be entered into the next process becomes clean and can be processed consistently both in the R application and data mining processing in Orange Software.

Data mining is an activity to explore and find the hidden knowledge in the database (Witten, 2011). Data mining is carried out through semi-automatic process stages that use statistical techniques and machine learning to extract and identify potential knowledge that can be very useful to get conclusions as material for decision making.

The researcher was using logistic regression method and measure Z test score by using R application to get the significancy value of relationship between independent variable and dependent variable.

For predictive analysis, the researcher was using Orange version 3.8 software, the data entered into this data mining process will then be modeled using Logistic Regression. Some parameters that will be used to predict and assess some of result values consist of prediction value, AUC (Area Under Curve) value, Accuracy Classification Score, Precision Score, Recall Score, and F1 Score.

RESEARCH RESULT

Result of Z Test Score

Test of significance or Z test in this research was carried out to know how far the effect of independent variable toward dependent variable. The condition was if the significance value was smaller than $\alpha = 0.05$, the hypothesis was accepted, which meant each independent variable could affect the dependent variable, otherwise the hypothesis would be rejected.

The model, namely service categorization and symptom group as independent variables, meanwhile system disruption as dependent variable, by using R application, the following result are visualized in table 2:

Table 2. Result of Z Test Score

Model	Chi square	Df	Pr(>Chisqr)	Signif. code
Service Categorization	1334.8	33	< 2.2e-16	***
Symptom Group	7002.2	77	< 2.2e-16	***

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

Model evaluation could be seen from Z test score, where significance value for all independent variables were 0.000 less than 0.05 which meant that both of them service categorization and symptom group variable showed significant effect to the system disruption.

The effect of service categorization toward the system disruption was significance with the value of 0.000 smaller than 0.05. Thus, the H1 hypothesis could be accepted and it was significant.

The effect of symptom group toward the system disruption significance with the value of 0.000 smaller than 0.05. Thus, the H2 hypothesis could be accepted and it was significant.

Result of Accuracy Test

The accuracy test result of the model are visualized in table 3 :

Table 3. Result of Accuracy Test

Model	Accuracy value
Service Categorization + Symptom Group -> System Disruption	0.6366124

From the model accuracy test, it could be seen that the accuracy value was 0.6366124 (63.66%) which meant that the independent variable in the model (service categorization and symptom group) was able to explain the system disruption percentage variable for 63.66% while the remaining 36.34% was explained by the variable outside of the model.

Probability Analysis Result

Probability analysis was using Orange software 3.8 to obtain the value for the model with logistic regression method. The following are the analysis result :

Table 4. Test Score of The Model

Model	AUC	CA	F1 Score	Precision	Recall
Service Categorization + Symptom Group -> System Disruption	0.906	0.536	0.022	0.186	0.012

Copyright © 2019

Leena and Luna International, Chikusei, Japan.
(株) リナアンドルナインターナショナル, 筑西市,日本
ISSN: 2186-845X ISSN: 2186-8441 Print
www.ajmse. leena-luna.co.jp

From the test score table, we get the AUC (Area Under Curve) value of the model was 0.906, it means the quality of the model was very strong (90.6%). The CA (Accuracy Classification Score) value of the model was 0.536 (53.6%), it means good. The F1 Score (Balance score between precision and recall score) value was 0.022 (2.2%), it indicates not good. The Precision valus of the model was 0.186 (18.6%), it indicates not good which means only some of system disruption types could be predicted very well, while another system disruption types were wrong predicted and wrong mapping.

The confusion matrix result of the model visualized in Table 5 :

Table 5. Confusion Matrix of The Model

		PREDICTION											
		A	B	C	D	E	F	G	H	I	J	K	L
A	A	1.2%	2.8%	1.6%	0%	0%	0%	0%	7.1%	0%	83.8%	3.5%	0%
	B	0.1%	83.5%	2.9%	0%	0%	0%	0%	0.3%	0%	2.7%	10.2%	0%
C	C	0.1%	48.7%	35.7%	0%	0%	0%	0%	1.6%	0%	13.3%	0.6%	0%
	D	0%	50.0%	8.7%	0%	0%	0%	0%	0.6%	0%	32.0%	8.7%	0%
T	E	0%	4.7%	0.9%	0%	0%	0%	0%	0.4%	0%	6.7%	87.3%	0%
	F	1.6%	58.8%	0.4%	0%	0%	0%	0%	2.4%	0%	36.8%	0%	0%
U	G	1.6%	4.8%	46.8%	0%	0%	0%	0%	4.8%	0%	17.7%	24.2%	0%
	H	1.1%	81.9%	5.4%	0%	0%	0%	0%	2.3%	0%	9.1%	0.2%	0%
A	I	0%	53.7%	6.9%	0%	0%	0%	0%	0%	0%	5.2%	34.2%	0%
	J	0.4%	1.3%	1.3%	0%	0%	0%	0%	2.1%	0%	95.0%	0%	0%
L	K	0%	14.2%	1.0%	0%	0%	0%	0%	0.1%	0%	5.4%	79.3%	0%
	L	2.2%	20.0%	0%	0%	0%	0%	0%	11.1%	0%	66.7%	0%	0%

Table 6. Prediction vs Actual of The Model

Type of System Disruption	**Prediction vs Actual Value**
A : Custom Reporting Problem	1.2%
B : Activation Error Problem	83.5%
C : Card Or Voucher Invalid	35.7%
D : Wrong Billing Charging	0%
E : Payment System Problem	0%
F : Electronic Money System Problem	0%
G : Job schedulling Problem	0%
H : User Access Problem	2.3%
I : Active Period Extension Problem	0%
J : USSD System Problem	95%
K : Block Unblock System Problem	79.3%
L : Loyalty System Problem	0%

In the results shown in Table 5 and Table 6, the horizontal label is a prediction, the vertical label is the actual.

It was found that for activation error problem case has 83.5% predicted value which meant 83.5% of activation error problems are matched between prediction compared to actual, it could be predicted very good.

For USSD (Unstructured Supplementary Service Data) system problem case has 95% predicted value which means 95% of USSD (Unstructured Supplementary Service Data) system problem case are matched between prediction compared to actual, it could be predicted very good. For block unblock system problem has 79.3% predicted value which means 79.3% of block unblock system problem are matched between prediction compared to actual, it could be good predicted. Meanwhile for other cases could not be predicted properly.

The researcher conducts further analysis of other values greater than 50% that do not match between prediction vs actual as described below :

Table 7. Table USSD System Problem vs Custom Reporting Problem

		Prediction
		USSD System Problem
Actual	Custom Reporting Problem	83.8%

The result in Table 7 means 83.8% that recorded in the system as custom reporting problem had been predicted as USSD system problem, meanwhile the remaining 16.2% had been predicted as other cases.

Table 8. Table Activation Error Problem vs Wrong Billing Charging

		Prediction
		Activation Error Problem
Actual	Wrong Billing Charging	50.0%

The result in Table 8 means 50.0% that recorded in the system as wrong billing charging had been predicted as aactivation error problem, meanwhile the remaining 50.0% had been predicted as other cases.

Table 9. Table Block Unblock System Problem vs Payment System Problem

		Prediction
		Block Unblock System Problem
Actual	Payment System Problem	87.3%

The result in Table 9 means 87.3% that recorded in the system as payment system problem had been predicted as block unblock system problem, meanwhile the remaining 12.7% had been predicted as other cases.

Table 10. Table Activation Error Problem vs Electronic Money System Problem

		Prediction
		Activation Error Problem
Actual	Electronic Money System Problem	58.8%

The result in Table 10, means 58.8% that recorded in the system as electronic money system problem had been predicted as activation error problem, meanwhile the remaining 41.2% had been predicted as other cases.

Table 11. Table Activation Error Problem vs User Access Problem

		Prediction
		Activation Error Problem
Actual	User Access Problem	81.9%

The result in Table 11 means 81.9% that recorded in the system as user access problem had been predicted as activation error problem, meanwhile the remaining 18.1% had been predicted as other cases.

Table 12. Table Activation Error Problem vs Active Period Extension Problem

		Prediction
		Activation Error Problem
Actual	Active Period Extension Problem	53.7%

Copyright © 2019

Leena and Luna International, Chikusei, Japan.
(株) リナアンドルナインターナショナル, 筑西市,日本
ISSN: 2186-845X ISSN: 2186-8441 Print
www.ajmse. leena-luna.co.jp

The result in Table 12 means 53.7% that recorded in the system as active period extension problem had been predicted as activation error problem, meanwhile the remaining 46.3% had been predicted as other cases.

Table 13. Table USSD System Problem vs Loyalty System Problem

		Prediction
		USSD System Problem
Actual	Loyalty System Problem	66.7%

The result in Table 13 means 66.7% that recorded in the system as loyalty system problem had been predicted as USSD system problem, meanwhile the remaining 33.3% had been predicted as other cases.

DISCUSSION AND CONCLUSION

Based on the analysis data result, it was summarized as follows:

a. The service categorization had significant effect to system disruption.

b. The symptom group had significant effect to system disruption.

c. The accuracy of the model (service categorization + symptom group toward system disruption) was good (63.66%), while the remaining 36.34% was explained by the variable outside of the model.

d. The result of prediction from 12 system disruption types shown that 3 of 12 could be predicted very well, that are 83.5% activation error problem matched with the actual problem, 95% USSD System Problem matched with the actual problem, and 79.3% block unblock system problem matched with the actual problem. Meanwhile the other cases could not be predicted well.

e. 83.8% of custom reporting problem had been predicted as USSD (Unstructured Supplementary Service Data) system problem.

f. 50.0% of wrong billing charging problem had been predicted as activation error problem.

g. 87.3% of payment system problem had been predicted as block unblock system problem.

h. 58.8% of electronic money system problem had been predicted as activation error problem.

i. 81.9% of user access problem had been predicted as activation error problem.

j. 53.7% of active period extention problem had been predicted as activation error problem.

k. 66.7% of loyalty system problem had been predicted as USSD (Unstructured Supplementary Service Data) system problem.

There are some limitations associated with the current research. There are no comparasion between one Telco Company to another. Data were collected only from service request management system in one ABC Telco Company in Indonesia. Therefore, the data have relatively homogenous characteristics and interests, as well as the result may vary to be applied in other countries or other business with different organization from different countries.

In the next phase of research or similar research, need to explore more variables on service request management that could effect the occurance of system disruption, so the research should be better and more comprehensive.

REFERENCES

[1] Bon, J. V. (2007). *IT service management an introduction.* USA: Van Haren Publishing.

[2] Dhillon. (1986). *Human reliability: With human factors.* USA: Pergamon Press.

[3] Heizer. (2006). *Operations management.* London: Pearson Education, Inc.

[4] Indrawati, P. (2015). *Management and business research methods*. Bandung: PT. Refika Aditama.

[5] IT GEIT Global Status Report. (2011). *Global Status Report GEIT 2011*. Retrieved from http://www.isaca.org/Knowledge-Center/Research/Documents/Global-Status-Report-GEIT-2011_res_Eng_0111.pdf.

[6] Ltd, I. T. (2017). *ITIL- Information technology infrastructure library*. Retrieved from https://www.itgovernance.eu/itil.

[7] Primadewi, T., Widjasena, B., & Wahyuni, I. (2014). Faktor-faktor utama penyebab human error dalam kecelakaan pada operator alat berat bergerak di tambang bawah tanah PT. *Jurnal Kesehatan Masyarakat*.

[8] Reason, J. (1990). *Human error.* UK: Cambridge University Press.

[9] Sudiro, A. (2012). *Modul 5 metodologi penelitian bisnis*. retrieved from modul 5 metodologi penelitian bisnis. Retreived from http://achmadsudirofebub.lecture.ub.ac.id/2012/02/modul-5-metodologi-penelitian-bisnis/.

[10] Witten, I. H.. (2011). *Data mining: Practical machine learning tools and techniques.* USA: Morgan Kauffman.

Copyright © 2019

Leena and Luna International, Chikusei, Japan.
(株) リナアンドルナインターナショナル, 筑西市,日本
ISSN: 2186-845X ISSN: 2186-8441 Print
www.ajmse. leena-luna.co.jp