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THE IMPLEMENTATION OF CREDIT RISK SCORECARD MODEL TO IMPROVE THE ASSESSMENT OF CREDITWORTHINESS IN A PEER-TO-PEER LENDING COMPANY

Rendy Franata[1], Taufik Faturohman[2] and Raden Aswin Rahadi[3]

[1] MBA Graduate, School of Business and Management, Institut Teknologi Bandung, email: rendy.franata@sbm-itb.ac.id
[2] Lecturer at School of Business and Management, Institut Teknologi Bandung, email: taufik.f@sbm-itb.ac.id
[3] Lecturer at School of Business and Management, Institut Teknologi Bandung, email: aswin.rahadi@sbm-itb.ac.id

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Abstract: *The most common problem in the financial service industry is the risk problem. One of the most crucial risk problems is default risk. Nowadays, the users of peer-to-peer (P2P) lending companies are growing rapidly; however, the companies have not prepared an adequate system to assess them. Furthermore, the company must have a different assessment model for each other. One assessment model which is currently used by the companies is 5C Credit Analysis. Through this research, the author constructs a credit scoring model which is based on the historical data to be implemented in a P2P lending company. The data used come from a P2P lending company in Bandung, Indonesia. The author chooses the Credit Risk Scorecard Model to predict the customer's creditworthiness assessment. The result indicates the model constructed is better than 5C Credit Analysis. It is shown by the Pearson correlation value, where the model generates higher significant value than 5C's Credit Analysis. Moreover, the model is tested using cross-validation test and resulted the optimum is occurred in the proper cut-off value of 0.235 with the accuracy rate, sensitivity rate, and misclassification rate, respectively as for 69.84%, 77.27%, and 28.24%. Moreover, the result is almost similar to the previous study which is used as the literature in this research.*

Keywords: *Credit Risk Management, Credit Scorecard, Creditworthiness, Logistic Regression, P2P Lending*

Introduction

Nowadays, the internet is the most critical aspect in supporting our activities. Internet plays an essential role in every aspect related to the utilization of technology and innovation (Apăvăloaie, 2014). This is followed by the extensive use of mobile devices that are entirely dependent on the internet connection. The presence of the internet has dramatically changed the magnitude of various aspects of life through digital transformation. The digital transformation in financial service industries made customers more convenience and trust in tech-based financial solutions. It is not only a business trend but also the representation of a revolutionary approach to making a business concept. There are changes in how information is used. How it attracted the customers' interest by meeting the customer demands with low cost, to transfer money, borrow, invest, and other financial products.

The digital transformation is supported by the internet development in a country. Currently, according to APJII (2017), the penetration of internet user in Indonesia is about 54.68% of the total population, the number always increase yearly. It is contrary to the financial inclusion level in Indonesia, where it is only 36% number of adults in Indonesia who own account transaction. This indicator indicates more than half of adult in Indonesia are unbanked (World Bank, 2014). There are several possibilities affect it, according to (Kabakova & Plaksenkov, 2018), financial inclusion is influenced by three configurations of factors, and those are: high socio-demographic and political factors without economic development; high social, technological and economic factors without political development; and political and economic factors without social and technological development. Both of the digital transformation era and the low of financial inclusion level in Indonesia are a golden opportunity for the financial service industry. According to (Ozili, 2018), digital transformation in financial service through Fintech gives a positive impact to support financial inclusion in developed and developing countries. An individual with low income needs the convenience of digital transformation more than the services from conventional banking which offer the similar facilities in higher cost and complicated requirements.

Credit risk is an essential aspect for a financial institution in running its business. One of the problems related to the credit risk is the customer's default risk. It is impossible to have no bad customers in the financial service industry, but the company must have their strategy to minimize the risk. The presence of digital transformation in financial service makes the industry must be better prepared to deal with various risks. Since the convenient access to the financial service makes the loan application rapidly increasing. The traditional system must be inadequate to ensure the business running well. The huge of customer's data processing needs an automatization to avoid the time-consuming process. The credit risk management needed to support the business. The way to deal with this problem is by constructing the credit scoring system. The system is such as a computerized procedure which attributes to grant the credit application process. The system assesses the customer's application in term of credit score, where there is a cut-off value to filter the granting process.

The peer-to-peer lending company is a new entrant in the financial service industry. It could offer certain benefits to both borrowers and lenders. The advantages of a P2P lending company for both of them such as the borrowers can get the loan facility directly from lenders, so that the rates may be lower than conventional banking service (Rosavina & Rahadi, 2018). While, the lenders can earn higher rates of return compared to any other type of lending such as corporate bonds, bank deposits or certificate of deposits (Emekter et al., 2015). The company concerns to serve the loan installment in the form of technology platforms. Currently, the company’s name is getting widely known, and the number of people applying for loans to the company is increasing; however, the companies have not prepared an adequate system to assess their customer's creditworthiness. A P2P lending company must have different assessment model to the peer companies. One assessment model which is currently used by the companies is 5C Credit Analysis. This model is still not fully automatic in assessing the customer's creditworthiness. It still needs the individual judgment in the credit granting process. This model is not efficient because it has many assessment items in it. This model also tends to generate errors since the process inside has much subjectivity. Misinterpretation the applicant's probability of default can lead to unreasonable rating, incorrect pricing of financial instruments and thereby it was one of the causes of the recent global financial crisis (Gurný & Gurný, 2013). The company evaluates its credit system regularly to maintain its performance by using a trial and error method. However, the rapid growth of users who submit loan application will burden the current system to process it. Based on this background, the author is interested in analyzing the implementation of credit risk scorecard model in a P2P lending company.

Literature Review

Risk becomes a problem that arises in daily lives both in term of individual and company. In economic activities, the risk event is leading to financial losses. The risk management is needed to avoid the risk problem occurred in a company (IACOB, 2014). Credit risk is the most critical problem which is commonly occurred in a financial service company. The term of credit risk refers to the risk of unrepaid for the amount of owed money. It has commonly occurred in the banking industry. It is the most critical aspect in a financial transaction since a long time ago (Gestel and Baesens, 2008). Recently, credit risk management concept has become very important in financial institutions to minimize credit risk in a company. (Muhamet & Arbana, 2016). Credit risk management in the financial service industry can be used to determine the level of risk of a borrower so that the risk of failure in repayment in the future can be prevented (Konovalova et al., 2017).

Credit scoring is one of loan evaluation methods which is commonly used in the banking industry. Previously, the credit granting process was taken by a specialized person who acts as the judgment for each's loan application. Since it is a time-consuming process, then the credit scoring system emerge. It works such a computerized procedure by using a set of programs which attribute the applicants' many points or score for their relevant characteristic (Steenackers & Goovaerts, 1989). Credit scoring uses a quantitative method of the actual payment and characteristics of past loans to predict the creditworthiness of a prospective applicant with similar characteristics (Schreiner, 2000). The model of credit scoring can help banks in deciding on credit granting process. The credit scoring model is used by commercial banks to assess the borrower's creditworthiness in requesting for loan facilities (Samreen et al., 2013). The development of credit scoring model is significant since there are many competitions and bad debt problems in the field of credit industry (Chuang and Lon, 2009). The development of credit scoring uses the historical data and statistical or machine learning technique to quantify the credit risk associated to the borrowers (Tripathi et al., 2018). The lower score indicates, the worse repayment performance, while the higher score indicates, the better repayment performance (Avery et al., 2009). Van Gool et al. (2011) state that the development of powerful risk management tools becomes more than ever crucial to survive. In their research, they analyze whether microfinance institutions can benefit from credit scoring, which has been successfully adopted in retail banking. Furthermore, from the creditor's side, creditors approve the customers who are expected capable of repaying their financial obligation and vice versa. Creditors can construct the classification rules based on the data of the previously accepted and rejected applicants (Chen & Huang, 2003).

The most crucial aspect in developing the credit scoring system is the technique of modeling selection. The selection process to find the appropriate model depends on the organization's policies and procedures. The models certainly cannot be applied immediately without any adjustment per the company's guidelines. There are many ways to establish a credit score system, according to (Gestel and Baesens, 2008), the credit scoring can be built in the form of a financial model, empirical data-based model, and expert model. Yap et al. (2011) used the empirical data-based model to establish the scoring model in their research. They find that the using of historical data on payments, demographic characteristics and statistical techniques, credit scoring models can help identify the essential demographic characteristics related to credit risk and provide a score for each customer. Dong et al. (2010), they propose a logistic regression model with random coefficients for building credit scorecard. They stated the logistic regression model is the most commonly used in the banking industry due to its desirable features (e.g., robustness and transparency).

According to Siddiqi (2005), credit risk scorecard seems like other predictive models, is used as a tool in the customer's level of risk evaluation. It does not identify the customer's tendencies to be a good or bad behaviour individually, but it provides statistical parameters namely odds, that is the probability that an applicant by its score then represented it will be “good” or “bad” later on.

Methodology

Conceptual Framework

Per Grant & Osanloo (2014), the conceptual framework is the author’s framework of thinking in exploring a specific issue, definite steps to do, and explain those different variables relationship serve in research. The framework used in this study is to explain the business issues that arise in the development of solutions to the issues raised in the business issues. The framework in the form diagrams to show the relationship between each concept that applied in this research.

Based on Figure 1 below, the conceptual framework is started with a business issue. The issue will be the primary concern to achieve the research objective. Generally, the literature about corporate risk is applied in this research. The corporate risk divided into four: financial risk, operational risk, strategic risk, externality risk. The financial risk consists of market risk, liquidity risk, credit risk, and funding risk. The business issue in this research mainly will be explained by applying the literature on credit risk management. The credit risk management will be performed by constructing credit scoring method using credit scorecard model. The credit risk scorecard is a model that has been used by a variety of industries for uses including predicting delinquency nonpayment, that is: bankruptcy, fraud, claims (for insurance), and recovery of amounts owed for accounts in collections. The scoring methodology offers an objective way to assess risk, and also a consistent approach, provided that system overrides be kept to a minimum. There are two main processes to establish the credit scorecard method. Those are the analysis of the weight of evidence and information value and the logistic regression. The weight of evidence and information analysis can be done through Microsoft Excel, while the logistic regression analyzed through SPSS. The results from each process subsequently used to construct the credit scorecard model formulation.

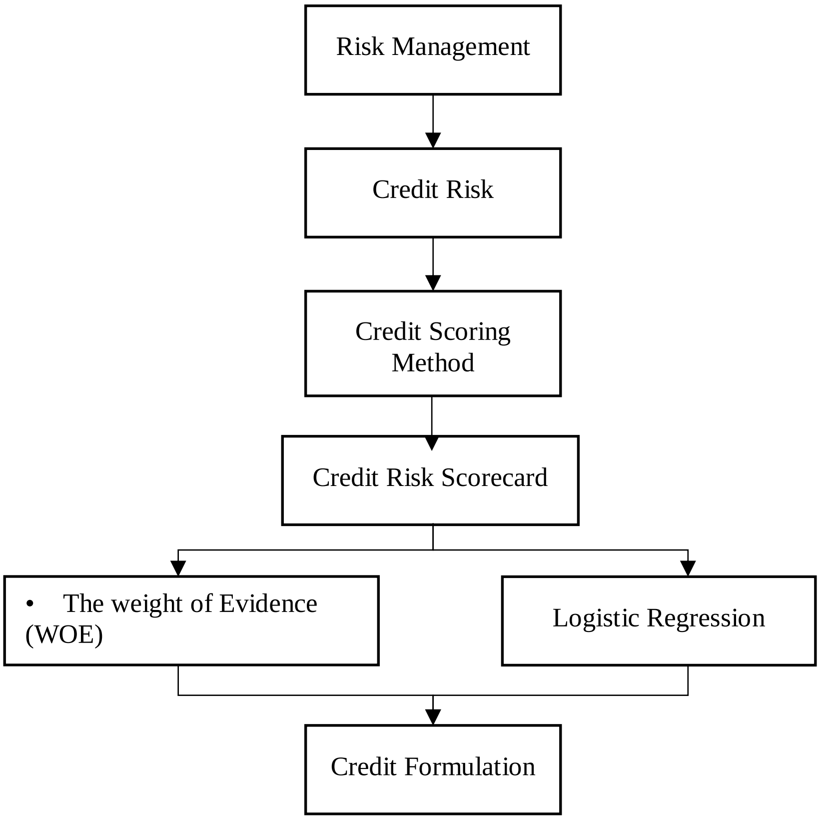

Figure 1: Conceptual Framework

Data Collection

In the data collection stage, the data is obtained from the P2P lending company in Bandung, Indonesia. The data obtained is the historical data of approved customers which is sent by email in the form of raw data. There are 170 customer's data successfully collected in this research which are then grouped into 12 variables to construct the model

Data Classification

In this stage, the collected data then classified into several variables. There are 11 variables act as independent and a variable acts as a dependent variable. The classification for each variable is shown in Table 1.

Data Processing

The first is calculate the weight of evidence aspect for each category in independent variables. High negative values, therefore, correspond to high risk, while high positives values correspond to low risk. So that, we can consider that the category with the highest negative WOE as the first category, while the highest positive WOE as the last category. The first category in each variable is served as the reference category means the category to which we compare the other categories. The next stage is calculating the IV aspect, and the last is logistic regression aspect.

Table 1: List of Variable

Variable Description	Variable Name	Coding	Category	Role	Measurements
The output of a customer's creditworthiness assessment	Behavior	0	Non-Default	Dependent	Binary
		1	Default		
The age in years	Age	1	47-57	Independent	Ordinal
		2	37-46		
		3	27-36		
		4	17-26		
Gender: Male and Female	Gender	1	Female		
		2	Male		
The ownership of any securities	Collateral	1	No		
		2	Yes		
Marital Status	Marital	1	Widower		
		2	Married		
		3	Single		
The dependency ownership	Dependent	1	No		
		2	Yes		
Address matching between ID card and application	Address	1	No		
		2	Yes		
Type of work	Employment	1	Other		
		2	Guru		
		3	Employee		
		4	Supervisor		
		5	Entrepreneur		
		6	Manager		
Amount of Instalment	Installment	1	>= 5.000.000 IDR		
		2	3.500.000 IDR - 4.999.999 IDR		
		3	2.500.000 IDR - 3.499.999 IDR		
		4	1.500.00 IDR - 2.499.999 IDR		
		5	0 IDR - 1.499.999 IDR		
Monthly Income	Income	1	0 IDR - 2.000.000 IDR		
		2	2.000.001 IDR - 4.500.000 IDR		
		3	4.500.001 IDR - 7.000.000 IDR		
		4	> 7.000.000 IDR		
Credit Duration	Tenor	1	7-12 Months		
		2	1-6 Months		
District of address	District	1	Kabupaten Cianjur		
		2	Other		
		3	Kabupaten Bandung		
		4	Kota Bandung		
		5	Kabupaten Bekasi		

Table 2: WOE and IV Result

Variable Name	Coding	Category	WOE	IV	Decision
Age (Years)	1	47-57	-0.291	0.080	Rejected
	2	37-46	-0.167		
	3	27-36	-0.214		
	4	17-26	0.351		
Gender	1	Female	-0.104	0.005	Rejected
	2	Male	0.052		
Collateral	1	No	-0.059	0.002	Rejected
	2	Yes	0.038		
Marital	1	Widower	-1.179	0.144	Input
	2	Married	-0.212		
	3	Single	0.467		
Dependent	1	No	-0.080	0.008	Rejected
	2	Yes	0.099		
Address	1	No	-0.546	0.146	Input
	2	Yes	0.271		
Employment	1	Other	-0.486	0.194	Input
	2	Guru	-0.331		
	3	Employee	0.431		
	4	Supervisor	-0.080		
	5	Entrepreneur	0.613		
	6	Manager	0.526		
Instalment	1	>= 5.000.000 IDR	0.667	0.135	Input
	2	3.500.000 IDR - 4.999.999 IDR	-0.034		
	3	2.500.000 IDR - 3.499.999 IDR	0.390		
	4	1.500.00 IDR - 2.499.999 IDR	-0.405		
	5	0 IDR - 1.499.999 IDR	0.134		
Income	1	0 IDR - 2.000.000 IDR	-0.996	0.351	Input
	2	2.000.001 IDR - 4.500.000 IDR	-0.185		
	3	4.500.001 IDR - 7.000.000 IDR	0.571		
	4	> 7.000.000 IDR	1.019		
Tenor	1	7-12 Months	-0.403	0.466	Input
	2	1-6 Months	1.201		
District	1	Kabupaten Cianjur	-1.051	0.662	Input
	2	Other	0.325		
	3	Kabupaten Bandung	0.495		
	4	Kota Bandung	0.836		
	5	Kabupaten Bekasi	0.901		

From Table 2 above, there are seven variables selected to enter the model. However, it is not the final model, only the variable with *a p-value* < 0.05 entitled to enter the final model. The final result of logistic regression is described in Table 3.

Table 3: Logistic Regression Result

		B	S.E.	Wald	df	Sig.	Exp(*B*)
Step 1a	Marital	-1.247	0.479	6.759	1	0.009	0.287
	Address	-1.459	0.498	8.594	1	0.003	0.233
	Income	-0.882	0.293	9.053	1	0.003	0.414
	Tenor	-1.127	0.566	3.973	1	0.046	0.324
	District	-0.746	0.189	15.538	1	0	0.474
	Constant	9.332	2.008	21.607	1	0	11293.195

From the information in the table above, we can write the equation as follows:

$$logit\left(\frac{p}{1-p}\right) = 9.332 - 1.247(A) - 1.459(B) - 0.882(C) - 1.127(D) - 0.746(E)$$

Where

A: the unit changes in marital variable
B: the unit changes in address variable
C: the unit changes in income variable
D: the unit changes in tenor variable
E: the unit changes in district variable

Scoring Calculation

The first step is to set the scaling format. In this research, the author considered that the probability terrible is 4:1. The value comes from the total sample: total events of default customers, 170:40 = 4.25:1, then rounded to be 4:1. So that, the author considered that the odds wanted is 4:1. The baseline score and point to double the odds (*pdo*) based on Siddiqi (2005), that is commonly used is the value of 500 and 20 respectively. The next step is to calculate the factor and offset value using the previous equation. The result is shown in Table 4.

Table 4: Scaling Format

Parameter	Value
odds	4
pdo	20
score	500
factor	$\frac{20}{ln(4)} = 28.85$
offset	$500 - (28.85 * ln(20)) = 460$

The next stage is to calculate the score point of each category. The score calculation result is shown in Table 5.

Table 5: Score Points

Variable	Category	WOE	Coefficient	Score
Marital	WIDOWER	-1.186	-1.282	-6
	MARRIED	-0.219		30
	SINGLE	0.476		55
Address	NO	-0.554	-1.469	14
	YES	0.273		49
Income	0 IDR- 2.000.000 IDR	-1.004	-0.888	12
	2.000.001 IDR - 4.500.000 IDR	-0.175		33
	4.500.001 IDR - 7.000.000 IDR	0.563		52
	> 7.000.000 IDR	1.011		64
Tenor	7-12 Months	-0.398	-1.108	25
	1-6 Months	1.193		76
District	KABUPATEN CIANJUR	-1.019	-0.742	16
	OTHER	0.318		45
	KABUPATEN BANDUNG	0.488		48
	KOTA BANDUNG	0.829		55
	KABUPATEN BEKASI	0.893		57

Cross-Validation Test

The last stage has tested the model. In this research, the model tested using cross-validation error test. This test is aimed to compare the predicting capability of models, where the capability to predict accurately the non-default borrower is named ‘‘accuracy rate”, the capability to predict accurately the default borrower is named ‘‘sensitive rate” and the model predicting accuracy rate is named ‘‘hit rate”. Initially, the model tested using cut-off value as for 0.5. There are two steps in this test. Those are the training sample and validation sample. Training sample is the model which is constructed by using 100% sample data, while the validation sample is the model which is constructed by using 50% sample data (selected independently). The result is shown in Table 6.

Table 6: The predicted result of logistic regression model-cutoff value is 0.5

Observed		Predicted		Corrected Rate
		Non-Default	Default	
Training Sample	Non-Default	125	5	96.15%
	Default	22	18	45.00%
			Hit Rate	84.12%
			Misclassification Rate	15.88%
Validation Sample	Non-Default	60	3	95.24%
	Default	9	13	59.09%
			Hit Rate	85.88%
			Misclassification Rate	14.12%

Therefore, it requires a validation to test the model robustness. The validation method is by setting the new fitted cut-off value ranging from 0.05 to 0.95, then plotting the result. The model is valid when the cut-off value generates the optimum result in all aspects of: accuracy rate, sensitivity rate, and hit rate. The plotting result from validation test is described in Figure 2.

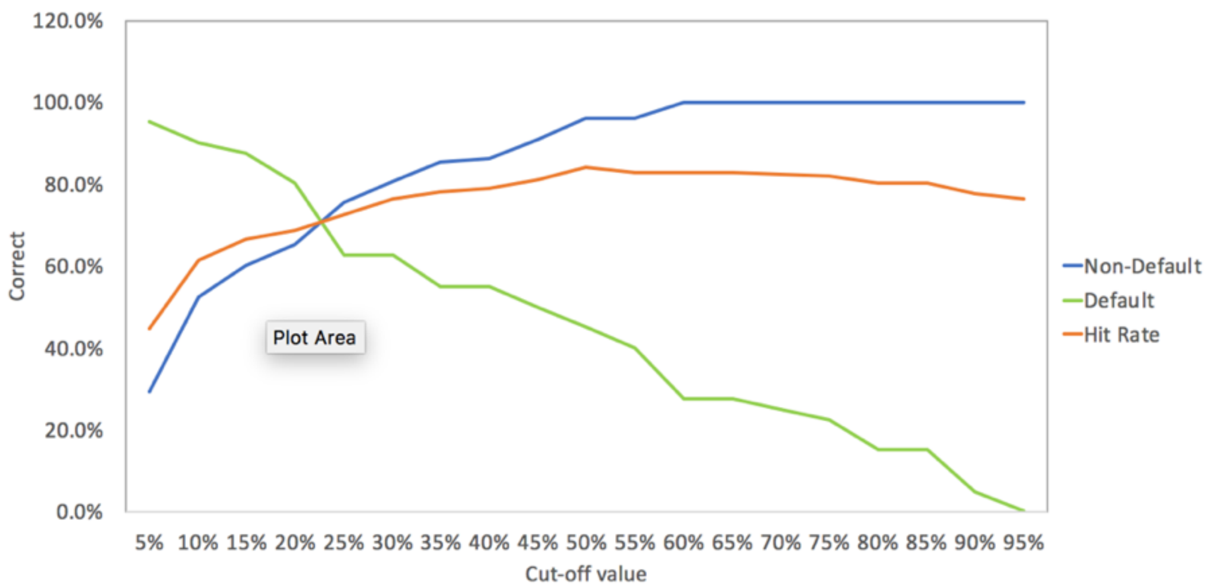

Figure 2: Fitted Cut-Off Value for Logistic Regression Model

From the chart above, the optimum point is in a cut-off value of 0.235. Then, it is tested using the cross-validation same as the previous step, and now the cut-off value is set as 0.235. The result is shown in Table 7.

Table 7: The predicted result of logistic regression model-cutoff value is 0.235

Observed		Predicted		Corrected Rate
		Non-Default	Default	
Training Sample	Non-Default	97	33	74.62%
	Default	13	27	67.50%
			Hit Rate	72.94%
			Misclassification Rate	27.06%
Validation Sample	Non-Default	44	19	69.84%
	Default	5	17	77.27%
			Hit Rate	71.76%
			Misclassification Rate	28.24%

From the table above, it indicates that the new fitted cut-off value (0.235) generates the lower hit rate and a higher misclassification rate. This new model must be worse than the model with cut-off value 0.5 if we compare the hit rate and misclassification rate parameters. If we take a look at the accuracy and sensitivity rate, this model has the optimum value where the accuracy rate is 69.84%, and the sensitivity rate is 77.27%. In this research, the higher sensitivity is considered as, the better model, since the sensitivity rate acts as the predictor of default customers. The model which will be constructed is preferred the model which is better in reducing the potency of real loss than the reducing the potency of opportunity loss. So that, the final model is the logistic regression with the cut-off value of 0.235.

Correlation (Pearson)

The model constructed is also compared to the company's scoring system. The comparison is carried out by using a Pearson correlation. The comparison result is shown in Table 8.

Table 8: Pearson Correlation

		Days Delayed	New Scoring	Old Scoring
Days Delayed	Pearson Correlation	1	-.286**	-.152*
	Sig. (2-tailed)		0	0.047
	N	170	170	170
New Scoring	Pearson Correlation	-.286**	1	-0.08
	Sig. (2-tailed)	0		0.3
	N	170	170	170
Old Scoring	Pearson Correlation	-.152*	-0.08	1
	Sig. (2-tailed)	0.047	0.3	
	N	170	170	170

From the table above, it found that the company’s existing assessment model has the Pearson correlation as for -0.152, while the new model in this research resulted in the value of is -0.286. The negative correlation means that there is an inverse relationship between the independent variables and the dependent variable. It can conclude that the credit scoring system resulted in this research has the stronger correlation than the company's existing assessment model.

Conclusion

Per research questions in chapter one, authors would answer them through the research conclusion. There are many ways to establish a credit scoring system, in this research the author has done construct the appropriate model for the P2P lending company, that is credit risk scorecard, to predict the customer's creditworthiness assessment. The model has met the excellent fit of criteria in term of WOE, IV, and *p-value*, so that, the output may not have deviated a lot from the model assumption. It is conducted the cross-validation test to check the model possibility to be the error. From the test, this model better using the proper cut-off value of 0.235

with the accuracy rate (69.84%), sensitivity rate (77.27%), hit rate (71.76%) and the misclassification rate (28.24%). According to Yap et al. (2011), their research results in the hit rate (72.05%) and misclassification rate (28.27%), while in Tsai et al. (2009), their research results in the hit rate (74.47%) and misclassification rate (25.53%). The model constructed in this research generates almost similar to the previous research. Then the model is compared to the company's assessment model, and the result is the new model is better in term of Pearson correlation than the existing assessment model.

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