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Identifying Relevant Predictor Variables for a Credit Scoring Model using Compromised-Analytic Hierarchy Process (Compromised-AHP)

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ABSTRACT

Developing an efficient credit scoring model to reduce the risk of personal-loan defaulters involves the selection of manageable reliable predictor variables in order to avoid the potential clients from providing too much information and to reduce the burden of a bank from keeping huge historical data, which can be burdensome and costly. The objective of this paper is therefore to illustrate how compromised-AHP can be used as one the methods to select such relevant reliable predictor variables before the final credit scoring model is constructed. A case study involving four experts from a bank was conducted. A set of sub-predictor variables under four main predictor variables namely financial indicators, demographic Indicators, employment indicators, and behavioural indicators was rated based on the perception of the four experts. The results reveal that, based on the experts' perception, the number of payments per year and payment interval, the loan or credit history, total income, total debt, the checking accounts, and age are the six most influential predictor variables while race, gender, and social status are the three least influential predictor variables.

Keywords:
Credit scoring model; predictor variables; loan defaulters; compromised-AHP

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1. Introduction

The banking industry has developed into one of the comprehensive and competitive markets in contributing to economic development over the past few decades. One of its many businesses is providing personal loans to potential clients. Giving out personal loans is an insecure business but at the same time, it is one of the major sources of income to most banks. Banks would prefer not to allow credit to those customers who lack the capacity to pay back the credit given. Be that as it may, after some time, a certain percentage of the credits will eventually transform into bad loan regardless of the possibility that the banks tighten its credit policy [1-2]. Analysing the non-performing loans data will effectively measure the quality of credit endorsement process. The loan granting process must be observed vigilantly, and banks should formulate an effective credit risk management. After

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all, many of the bad debts have been caused by the inappropriate conduct of approving new financing [2-4].

Currently the screening of whether a potential client's loan application should be approved or not is done through a credit scoring or credit risk model which is a decision analysis model with fundamental techniques to assist banks in deciding whether or not credit should be extended to an applicant of which will likely result in profits or losses [5-6]. The model is constructed through the utilization of various tools such as:

i. Statistical-based analyses such as linear regression [7], discriminant analysis [8-9], decision tree [10-13], and logistic regression [14-15,78].
ii. Artificial intelligence (AI)-based analyses such as genetic algorithm [16-20], simulated annealing [20-21], and neural network ([22-25,78]).
iii. Machine learning [16,21,26].

However, despite the thorough process, the probability of the client-loan defaulters can still be high, thus raising a question of whether the existing credit scoring model used to screen such potential defaulters is still reliable. The reliability of the existing credit scoring model may be influenced by two factors, namely, the factors/variables used in the model and the weights assigned to those factors/variables [77].

The selection of the right predictor variables to be included in any credit scoring model of choice is crucial because there are many potential predictor variables discussed in the literature. Since credit scoring models are built up using factual data derived from historical recorded data of real clients [6] it is impossible for a bank to be asking its potential clients to furnish all the information for all the available predictor variables. Thus, selecting a set of suitable and manageable predictor variables must be done very carefully.

The objectives of this paper therefore are to identify the potential key predictor variables that can be included in a credit scoring model as discussed in the literature, and to illustrate how the final suitable and manageable set of predictor variables can be determined from the potential key predictor variables to be included in a credit scoring model of choice based on the experts' evaluations via Compromised-AHP.

Studies have shown that a bank's business success and even survival depend to a large extent on the ability of the bank management to construct and implement sound policies on credit risk. Many delinquency problems could have been avoided if the management can ensure that the earlier lending processes are conducted correctly of which failure to comply will lead to lower credit scores and high likelihood of non-payment [27-28]. Thus, reviewing the key variables that should be included in the credit scoring model will lead to a better screening process with the hope to see improvement on asset quality in terms of impaired asset position, better management of credit risk, improvement of turnaround time for new application, and cost saving [16], which in all will cumulatively contribute to the development of bank efficiency and profitability. In addition, Compromised-AHP was selected since it offers the same rigor of AHP which is the pairwise-comparison-type evaluation but without the worry of having inconsistent pairwise-comparison matrices which happens to be one of the major issues when applying AHP.

2. Literature Review

Two aspects that are relevant to the objectives of this paper are reviewed here. The two aspects are the potential predictor variables that can be included in a credit scoring model of choice, and the suitable techniques that can be used to shortlist the relevant predictor variables to a manageable set.

2.1 Potential Predictor Variables to be Considered in a Credit Scoring Model

As mentioned earlier, the objective of credit scoring is to estimate, by experimental way, the risk of giving out loan to specific criteria of borrowers. This objective can be attained with a decision model that enables a bank to forecast future repayment trend of a candidate with identical attributes to historical data of past applicants. Variables containing the information of the characteristics of borrowers are then applied into the credit scoring model [2,29]. It is therefore important to develop a credit scoring model which consists of the right predictor variables. According to Vojtek and Kocenda [30], the variables can be separated into four different indicators which are financial indicators, demographic indicators, employment indicators, and behavioral indicators.

2.1.1 Financial Indicators

Financial indicators involve the financial status or position of the loan applicant in repaying the loan [31]. The indicators include total gross income [32,33,53], total asset [33-34], total debt [33,35.50,54,57], and collateral [36-37,51].

2.1.2 Demographic Indicators

Loan applicant's demographic indicators involve the characteristics of the applicant which among others cover age [38-39,47,48,50-54], marital status [2,47,50-52]), gender [2,47,50,54], race [2], number of dependents [40-42,47,50,52,53], and social status [43,52-54]

2.1.3 Employment Indicators

Employment indicators cover the industry and nature of work that the applicant involved in together with the employment and unemployment benefit [44]. Some of the important indicator variables discussed in the literature are type of employer [41,44,54,57], job position [45,54,57], length of year in current employment [43,46], and length of year in previous employment [2].

2.1.4 Behavioural Indicators

Potential client's behaviour is usually related to behaviour that is relevant to money management [31]. Thus, some of the potential indicator variables are the checking accounts [43,54,56],the number of payments per year and payment intervals [48,53,54,55,57]), and the loan/credit history [35,41, 49,55].

2.2 Techniques to Shortlist the Relevant Predictor Variables

The primary objective in credit scoring is to develop an effective scoring model which contains only a set of manageable predictor variables. The total number of predictor variables cannot be too large in order to avoid the bank from keeping too many information and to reduce the complexity of the credit scoring model as well as the cost of collecting the information [58]. There are many techniques that can be utilized to select a set of manageable predictor variables from the pool of predictor variables found from the literature before the final scoring model is developed.

For the case of identifying the suitable predictor variables for a credit scoring model, some of the more popular techniques are Elimination and Choice Expressing Reality (ELECTRE) [59-60], DEMATEL [61-62], Delphi method [63], and AHP [64-66]. Normally, the result will be in the form of the ranking scores of the predictor variables and in many instances the ranking as well as the scores differ from method to method [67]. Therefore, as the result may differ according to the model selected, it is relevant to establish the practical and managerial implications for selecting one model or the other [68].

2.2.1 Analytic Hierarchy Process

Analytic Hierarchy Process (AHP) is a technique that simplifies a complex problem by means of hierarchical analysis methodology, which enables subjective judgments among different predictor variables [69]. It has been used by various researchers and practitioners to build a credit risk assessment model [70-72]. Serrano-Cinca *et al.*, [71] claimed that AHP can assess the credit history of the applicant (past), accounting information and intangible assets from the loan applicant itself from the financial (present), and from the social point of view (future).
Basically, the steps in AHP are as follows [73]:
Step 1: Defining the problem and the predictor variables to be used.
Step 2: Implementing pairwise comparisons for each pair of the predictor variables (i, j) using a set of preference scale ranging from 1 to 9 as given in Table 1 and transfer those pairwise comparison values to a pairwise comparison matrix as shown immediately after Table 1.

Table 1
Preference scale for the AHP's pairwise comparisons

Preference Level	Numeric Value
Equally preferred	1
Equally to moderately preferred	2
Moderately preferred	3
Moderately to strongly preferred	4
Strongly preferred	5
Strongly to very strongly preferred	6
Very strongly preferred	7
Very strongly to extremely preferred	8
Extremely preferred	9

Note: When predictor variable *i* compared to *j* is assigned one of the above numbers, the predictor variable *j* compared to *i* is assigned its reciprocal.

$$C_{ij} = \begin{bmatrix} 1 & c_{12} & \cdots & c_{1,n-1} & c_{1n} \\ c_{21} & 1 & \cdots & \cdots & \cdots \\ \cdots & \cdots & 1 & \cdots & \cdots \\ \cdots & \cdots & \cdots & 1 & c_{1-n,1} \\ c_{n1} & \cdots & \cdots & c_{n,n-1} & 1 \end{bmatrix}$$

where c_{ij} = pairwise comparison value between predictor variable i and j.

Step 3: Normalizing the pairwise comparison matrix by taking the column sum and dividing each value in the pairwise comparison matrix by its column sum.
Step 4: Computing the average of the values in each row of the pairwise comparison normalized matrix.
Step 5: Checking the consistency of the pairwise comparison matrix by calculating the consistency ratio (*CR*-value) of the pairwise comparison matrix.

The *CR*-value can be calculated using formula 1:

$$CR = CI/RI \tag{1}$$

where CI = consistency index = $(\lambda - n)/(n\text{-}1)$, λ = the largest pairwise comparison matrix's eigenvalue, n = total number of predictor variables, and RI = random index which can be determined by referring to the *RI*-Table (Table 2).

Table 2
Random Index [69]

n	1	2	3	4	5	6	7	8	9	10	11	12
RI	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49	1.51	1.56

The pairwise comparisons must be repeated if the *CR*-value is bigger than 0.1. Otherwise, the pairwise comparison matrix is considered to be consistent, and the result obtained in step 4 will be the influence weight of each of the predictor variables in predicting loan-defaulters.

The possibility of getting an inconsistent pairwise comparison matrix is one of the main issues when dealing with AHP [74-75]. To tackle this inconsistency problem, [76] proposed a new Compromised-AHP technique which utilizes a Likert scale of 1 to 9 as a starting process.

2.2.2 Compromised-AHP

As mentioned earlier, Nazri *et al.*, [76] introduced Compromised-AHP as a mean to tackle the inconsistent pairwise comparison matrix in AHP. The simple approach of utilizing a Likert scale of 1 to 9 guarantees that the desired pairwise comparison matrix will always be consistent. The approach begins by asking the evaluators to rate the level of influence of each predictor variable on the problem to be solved using the scale of 1 to 9 whereby 1 represents "least influential" while 9 represents "extremely influential". Next, the evaluation values will be transformed into Saaty's AHP-pairwise comparison matrix $C = [c_{ij}]_{nxn}$ through a simple process as follows: Suppose that the evaluator rated predictor variable i as w_i and predictor variable j as w_j. Then c_{ij} which is the pairwise comparison value between predictor variable i and predictor variable j and can be interpreted exactly as proposed by Saaty [69] in Table 1 is determined using formula 2 given below [76].

Let $b = w_i - w_j$.

$$\begin{aligned} &\text{If } b > 0 \text{ then } c_{ij} = b+1; \\ &\text{If } b = 0 \text{ then } c_{ij} = 1; \\ &\text{If } b < 0 \text{ then } c_{ij} = 1/(1\text{-}b) \end{aligned} \tag{2}$$

Having obtained the pairwise comparison matrix, the rest of the steps will be exactly the same as the standard AHP steps.

3. Applying Compromised-AHP on the Predictor Variables: Steps Taken and Results Obtained

Applying Compromised-AHP [76], there are four steps involved towards identifying the manageable set of predictor variables. To illustrate the processes, a case study involving four senior expert officers from a bank in Malaysia was conducted. These four experts have had more than ten years of experience in dealing with the loan application approvals at the bank, thus justifying their inclusion for the evaluation of the predictor variables.

Step 1: Constructing the AHP-structure.

After a two-hour of brainstorming session, the four experts had agreed to consider all the predictor variables outlined in the literature review section in this study. As a result, the decision AHP-structure is as follows (Figure 1):

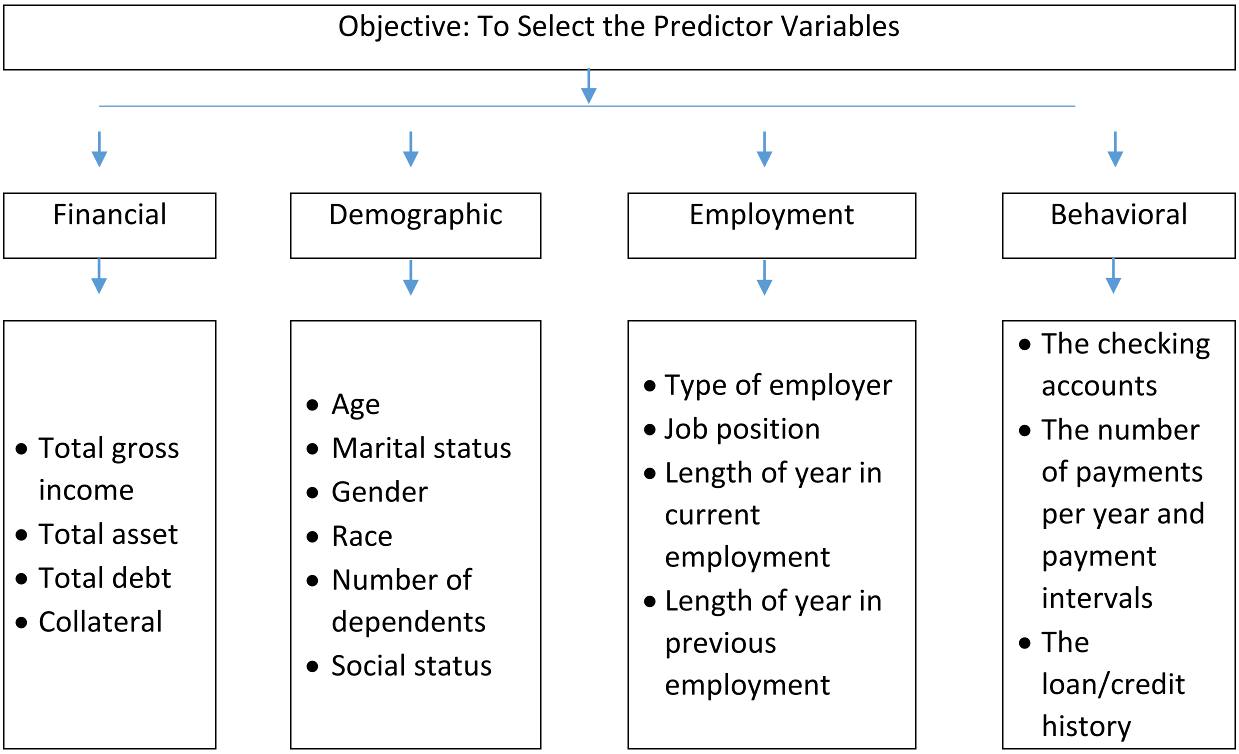

Fig.1. The AHP-structure for the problem

Step 2: Designing the questionnaire and collecting the data.

The same four experts were asked to rate their perception on how influential each main predictor variable and each sub-predictor variable under each main predictor variable in predicting the probability of a loan defaulter. Each of the experts gave his/her rating via a set of questionnaires attached in the appendix.
Step 3: Constructing the pairwise comparison matrix via Compromised-AHP.
Before constructing the pairwise comparison matrix, the group evaluation score was calculated by taking the simple arithmetic mean score of all the experts' evaluation score as suggested by Lootsma [6]. To illustrate the approach, we give an example involving the evaluation by the experts for the main predictor variables.
Firstly, the average rating score for each main predictor variable is as given in Table 3.

Table 3
The average rating score for the main predictor variables

Main Variable	Financial	Demographic	Employment	Behavioral
Mean Score	7.75	6	6.50	8

Next, applying formula (2), the pairwise comparison matrix $C_{\text{Main-ij}}$ for the main predictor variables was obtained.

$$C_{\text{Main-ij}} = \begin{array}{c} \\ \text{Financial} \\ \text{Demographic} \\ \text{Employment} \\ \text{Behavioral} \end{array} \begin{array}{c} \begin{array}{cccc} \text{Financial} & \text{Demographic} & \text{Employment} & \text{Behavioral} \end{array} \\ \begin{bmatrix} 1 & 2.75 & 2.25 & 1/1.25 \\ 1/2.75 & 1 & 1/1.50 & 1/3 \\ 1/2.25 & 1.50 & 1 & 1/2.5 \\ 1.25 & 3 & 2.5 & 1 \end{bmatrix} \end{array}$$

Step 4: Obtaining the final weight for each main predictor variable and sub-predictor variable under each main predictor variable.

The final weight that gives the level of influence each main predictor variable has on the probability of loan-defaulters based on the perception of the four experts was determined. The final weights are as given in Table 4. The *CR*-value obtained, i.e. *CR*-value = 0.00, proves that the pairwise comparison matrix is consistent.

Table 4
The final weight for the main predictor variables

Main Variable	Financial	Demographic	Employment	Behavioral
Total Weight	0.332	0.119	0.160	0.389
		CR-value = 0.00		

The results reveal that based on the perception of the four experts, behavioral indicators is the most influential main variable (total weight = 38.9%), followed by financial indicators (total weight = 33.2%), employment indicators (total weight = 16.0%) and finally, demographic indicators (total weight = 11.9%).

The same procedure was performed for the sub-predictor variables under each main predictor variable. The average rating score and the final weight the sub-predictor variables under each main predictor variable are given in Table 5, Table 6, Table 7, and Table 8. The total real weight for each sub-predictor variable which can be used as the sub-predictor variable's overall influential ranking with respect to all the other sub-predictor variables under all the four main predictor variables was also calculated using formula 3.

Total real weight for sub-predictor y under main predictor z = (*Total weight for sub-predictor y*) *x* (*Total weight for main predictor z*) (3)

Table 5
Mean score and final weight for the sub-predictor variables under "financial"

Sub-Variable	Total gross income	Total asset	Total debt	Collateral
Mean Score	8.25	6	7.5	5.25
Total Weight Under Sub-Variable	0.456	0.142	0.346	0.096
Total Real Weight	0.151	0.047	0.115	0.032
		CR-value =0.01		

Based on the perception of the four experts, total gross income is the most influential sub-predictor variables under the main-predictor variable, financial, with a total weight of 45.6%. This is followed by total debt (total weight = 34.6%), total asset (total weight = 14.2%), and collateral (total weight = 9.60%).

Table 6
Mean score and final weight for the sub-predictor variables under "demographic"

Sub-Variable	Age	Marital status	Gender	Race	Number of dependents	Social status
Mean Score	7.25	6	3.5	2.5	5.75	4.25
Total Weight Under Sub-Variable	0.380	0.218	0.068	0.045	0.192	0.097
Total Real Weight	0.045	0.026	0.008	0.005	0.023	0.011
			CR-value = 0.02			

Under the main-predictor variable demographic, the four experts are of the opinion that age is the most influential sub-predictor variable (total weight = 38.0%) followed by marital status (total weight = 21.8%). Gender is believed to be the least influential sub-predictor variable with a total weight of 6.8%.

Table 7
Mean score and final weight for the sub-predictor variables under "employment"

Sub- Variable	Type of employer	Job position	Length of year in current employment	Length of year in previous employment
Mean Score	7.5	7.5	6.75	5.25
Total Weight Under Sub-Variable	0.344	0.344	0.213	0.099
Total Real Weight	0.055	0.055	0.034	0.016
		CR-value = 0.00		

Type of employer and job position are perceived as equally most influential sub-indicator variables with a total weight of 34.4% each, followed by length of year in current employment (total weight = 21.3%) and length of year in previous employment (total weight = 9.9%).

Table 8
Mean score and final weight for the sub-predictor variables under "behavioral"

Sub-Variable	The checking accounts	The number of payments per year and payment intervals	The loan/credit history
Mean Score	7.25	8	8
Total Weight Under Sub-Variable	0.222	0.389	0.389
Total Real Weight	0.086	0.151	0.151
CR-value = 0.00			

Finally, under the main predictor variable behavioral, the four experts believed that the number of payments per year and payment intervals as well as the loan/credit history will influence the probability of the personal-loan defaulters the most with a total weight of 38.9% each. The checking account came in third (total weight = 22.2%).

4. Discussion and Conclusion

This paper presented a case study involving four experts from a bank in determining which predictor variables should be taken into consideration for the revision of an existing credit scoring model involving personal loan future clients. Compromised-AHP was utilized to determine the level of influence each predictor variable has on the probability of the personal loan defaulters. Based on the influential rating done by the four experts and the real total weights obtained, the number of payments per year and payment interval (real total weight = 15.1%), the loan or credit history (real total weight = 15.1%), total income (real total weight = 15.1%), total debt (real total weight = 11.5%), the checking accounts (real total weight = 8.64%), and age (real total weight = 4.52%) are the six most influential predictor variables. These six predictor variables contribute to 69.96% of the total weight 100%. Meanwhile, the four experts perceived race (0.53%), gender (0.809%), and social status (0.97%) as the three least influential predictor variables. With such ranking, the bank can now decide how many of these variables to be included in the new credit scoring model.

Based on the results of this study, two suggestions can be put forward on how a bank can implement its credit scoring model:

i. Continue with the existing credit scoring model while concurrently, start to require new potential clients to furnish the information pertaining to the additional new predictor variables that have not been included in the existing credit scoring model. Once enough information is gathered, the new credit scoring model can be developed and utilized.
ii. Contact all the existing clients to request for the needed new information and develop the new credit scoring model to be implemented as soon as possible.

This study is by no means, perfect. Firstly, not all the variables have been included in this study. Variables such as loan amount and history of relationship with the bank for example, were not considered. Thus, future studies should include such variables to be considered. Secondly, some of the predictor variables might correlate with each other. Neither compromised-AHP nor AHP would be able to detect the correlation among predictor variables. Thus, it would be interesting to see the outcome of this study had another approach that could detect some level of correlation among predictor variables is applied. One such technique is DEMATEL.

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