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APPLICATIONS OF PERFORMANCE SCORING TO ACCOUNTS RECEIVABLE MANAGEMENT IN CONSUMER CREDIT

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Abstract

Performance scoring offers credit grantors improved ability to manage their consumer loan portfolios. The analytical models on which performance scoring are based employ data from creditors' accounts receivable ledgers reflecting customer payments and purchases or data from credit reporting agencies. Collected at the "Observation Point," these data reflect the behavior of customers during the "Performance Period," usually the preceding six or 12 months. The performance scoring system based on this information is designed to predict customer payment performance in the future, the "Outcome Period."

Creditors have frequently determined historical "roll rates," that is, the percentages of customers moving from one stage of delinquency to another. Thus, a creditor may know that 25 percent of his customers who are one payment delinquent at the "Observation Point" will be one payment or more delinquent within the next month. However, knowledge of the roll rate permits a creditor to forecast movement of customers through various categories of delinquency only on an average basis. Rather than focus attention on all customers that are one payment behind, it would be more efficient for a credit grantor to direct collection efforts only to that group of customers most likely to remain delinquent or likely to become more seriously behind in their payments.

An illustration of how performance scoring permits creditors to focus on customers whose delinquency position is likely to worsen is provided using data developed from analysis of accounts in a bank credit card portfolio. Examples are based on past account behavior as well as on data from credit reports. A total of 10,000 accounts were one-month delinquent. However, under the performance scoring system based on account histories, only 2,000 accounts had a performance score of less than 50. Within this group of customers were included 55.7 percent of the customers that are expected to be one or two months delinquent during the next six months and 61.7 percent of the customers that will be three or more months delinquent during that period. Thus, by concentrating collection efforts on these accounts, a credit grantor will avoid antagonizing many customers likely to return to a current status and increase the likelihood of collecting from those whose delinquency is likely to worsen.

Performance scoring may be used for a wide variety of credit decisions-targeting collection efforts; making credit line changes and purchase authorizations, and cross-selling other financial services. As creditors both reduce the cost and improve the efficiency of these credit decisions, both consumers and credit grantors benefit.

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APPLICATIONS OF PERFORMANCE SCORING TO ACCOUNTS RECEIVABLE MANAGEMENT IN CONSUMER CREDIT

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I. Introduction

The purpose of this paper is to demonstrate the ability of analytical models to assist creditors in the management of their consumer loan portfolios. Past account payment and purchase data are used to predict future payment performance. Such forecasting models have the potential to assist creditors in collection efforts, credit line changes, purchase authorizations, termination of collection efforts and cross-product solicitation.

Consumer credit is extended by most retailers, banks, savings and loan associations, finance companies, credit unions and many other service companies. With the exception of credit unions, organizations extend credit to generate profit. Consumer credit is also very important to those who use it. The proper use of credit can allow consumers to raise their standard of living.

Two critical elements of the consumer credit process are (1) the evaluation of new credit applications and (2) the management of the accounts on an ongoing basis. Analytical modeling may provide useful management tools in both these areas. To date most of the academic literature and business applications have dealt with the new-account credit evaluation process. Numerous articles have been written on the application of "credit scoring" in forecasting creditworthiness [2] and many such risk forecasting models are used in the consumer credit industry. There has been little treatment in the literature of analytical models to assist in the ongoing management of the accounts. However, one noteworthy exception is the excellent overview of the topic by M.C. Blake [1].

Today, the ongoing management of accounts receivable may be an even more important topic than the credit evaluation process. Although each credit applicant is evaluated by a creditor when he or she applies for credit, there are many points for evaluation and decisions during the ongoing management of existing accounts. For example, a creditor must determine at least every billing cycle (typically monthly) which accounts require collection activity. In a revolving credit environment, decisions must be made at several points concerning purchase authorizations and requests to change credit limits. Further, the general make up of the United States population is changing. The distribution of ages is shifting upward as the birth rate slows. Creditors can not achieve the level of expansion of their loan portfolios that once was available by approving new applicants. Existing accounts must be managed more efficiently by reducing risk and expanding credit limits where warranted. Finally, as the available credit and purchase mechanisms (e.g., electronic funds transfers) become more complex and automated, more frequent and more timely decisions will be required.

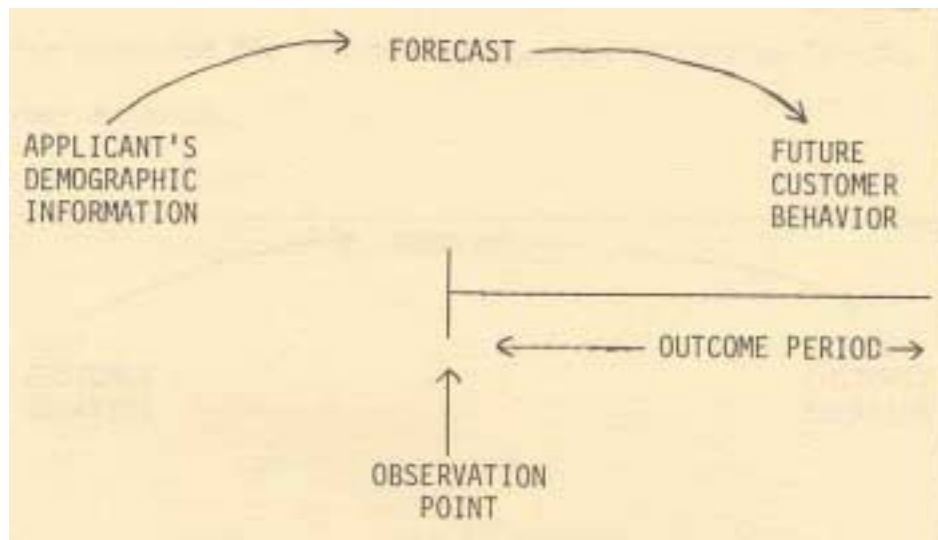
Creditors generally have determined relatively stable percentages of customers moving from one stage of delinquency to another. For example, a creditor may know that ten percent of the customers that are current at a given point in time will become one payment delinquent within the next month; or that 25 percent of the customers that are one payment delinquent at a point in time will be one payment or more delinquent within the next month. Although historical "roll rates" allow a creditor to forecast movement of customers through various categories of delinquency (and eventually charge off) on the average, the roll rates do not help to identify the specific customers that are most likely to become delinquent. Although a creditor may know that 500 out of 10,000 one-month delinquent customers may become credit losses within the next year, the creditor is not able to forecast the particular customers that are most likely to become losses without time-consuming and costly analysis of each of the 10,000 customers. The creditor is faced with the dilemma of doing nothing at early stages

of delinquency to minimize the eventual loss from the "high risk" customers or taking action (perhaps by reducing credit limits or initiating early collection activity) on all (or at least a very large subset) of the 10,000 one-month customers.

II. New Application Scoring vs. Performance Scoring

Credit scoring is a broad term that encompasses both new applicant scoring and performance scoring. The concept of performance scoring may best be explained by comparing it with new applicant scoring. New applicant scoring is the use of a numerical formula for predicting the creditworthiness of a new applicant by assigning points to specific applicant characteristics. The total of the points indicates the credit risk of the applicant.

The diagram below illustrates the objective of a new applicant scoring model and the information utilized to develop forecasts of customer behavior.



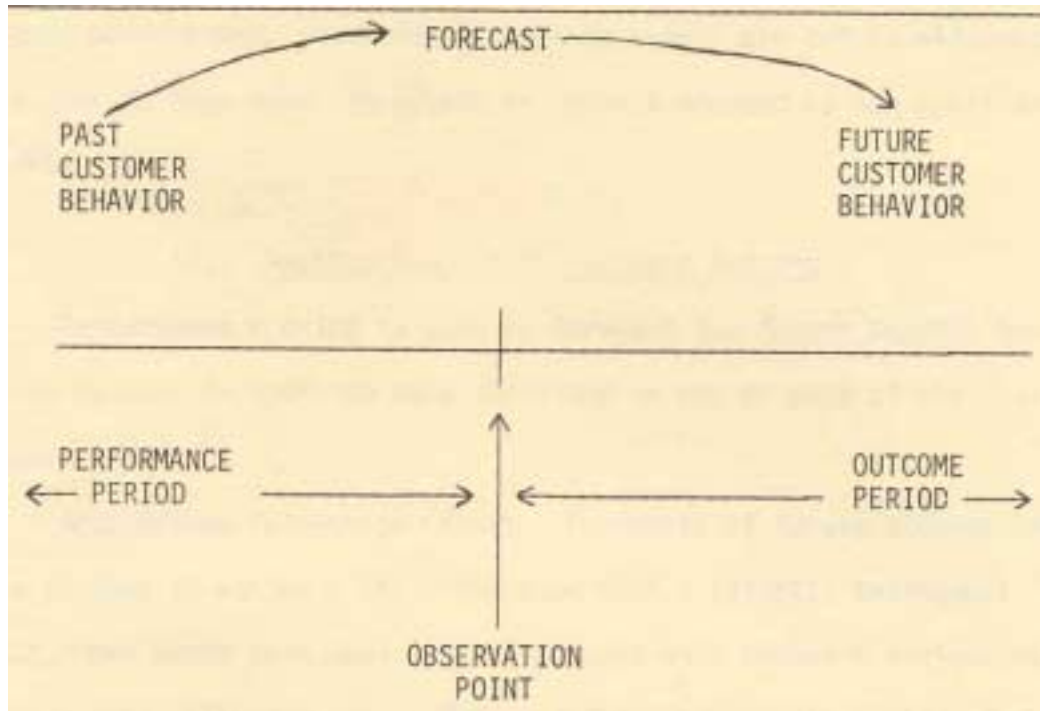
The objective of the new applicant-scoring model is to forecast the future behavior of a new credit applicant over a specified period of time known as the "Outcome Period." The future customer behavior generally is divided into two outcomes: the customer turned out to be "good" (profitable) or "bad" (unprofitable) over a relatively long time horizon (approximately two years or longer). The applicant is observed at a point in time (the "Observation Point"), and demographic information available at the time of observation is utilized to forecast future behavior. New applicant scoring is a widely used and accepted management tool.

Performance scoring is the use of a numerical formula for predicting the future payment performance of an existing account by employing past payment or purchase behavior. Performance scoring typically is applied to existing accounts to update forecasts of future performance on an ongoing basis.

The next diagram illustrates the objectives of a performance-scoring model and the Information utilized to develop forecasts of customer behavior.

As with new applicant scoring, the objective of performance scoring is to forecast future customer behavior for a specified period of time (the "Outcome Period"). However, the measures of performance generally relate to future delinquency status within a relatively short period of time (six to 12 months), and

customers may be divided into more than two outcome groups (for example, three or four possible outcomes measured by level of delinquency rather than simply "good" and "bad"). The customer is observed at a point in time (the "Observation Point"), and past customer behavior for some preceding period of time (the "Performance Period") is utilized to forecast the future customer behavior. Although the primary focus of performance scoring models is on the creditor's own previous experience with the customer over a period of time, payment behavior of the customer with other creditors (for example, credit report data) can also be utilized to forecast future performance. Performance scoring models are not in widespread use, nor do they have the common acceptance enjoyed by new applicant models.



III. Applications of Performance Scoring

Performance scoring is used to forecast the future payment behavior of an account in order to make decisions in one or more of the following areas:

Accelerated Collection Effort. Forecasts of future account behavior can be used to estimate the likelihood that a slightly delinquent (e.g., one month past due) loan or account will become a serious collection problem within the near future. The creditor can implement different collection strategies or take other appropriate action based upon the forecast of future account behavior.

Credit Limit Review and Purchase Authorization. Performance scoring can be used to predict the likelihood that a loan or an account will become a serious collection problem if a credit limit is raised or a purchase authorized.

Termination of Collection Effort. At some point in the normal collection process it is no longer profitable to continue internal collection efforts. The creditor is better off sending the account to a collection agency or to

an attorney for appropriate action. Performance scoring can be used to identify those delinquent loans or accounts that are very unlikely to become current.

Solicitation. A creditor may be interested in cross-selling one or more products to certain accounts within its existing portfolio. For example, a bank may wish to solicit a subset of its credit card customers for automobile loans. Again, performance scoring may aid in identifying a particular subgroup of accounts that are likely to qualify for the additional credit and, if accepted, likely not to become problem loans.

IV. Data Requirements

An adequate sample of accounts must be obtainable from the creditor's records. An Observation Point must be selected (usually six months to a year prior to the actual date of the study) and information regarding account behavior before and after that Observation Point must be available on the master file. Generally, a creditor must have retained a minimum of 12 and preferably 24 months of account activity in order to provide adequate data for the construction of a performance scoring system.

A separate sample of accounts is selected for each type of scoring model to be constructed. For example, if one model is to be developed to forecast future payment behavior for all accounts presently showing a "current" status (perhaps for the purpose of automatic credit limit review) and a second model is to be developed to forecast future payment behavior for all one-month delinquent accounts (perhaps for purposes of structuring the collection effort), a sample of accounts that were "current" at the Observation Point and a sample of accounts that were one-month-delinquent at the Observation Point would be selected. Each of these samples must be selected so that the outcomes fall into two or more approximately equal size groups: loans or accounts that remained current during the Outcome Period and loans or accounts that attained specified levels of delinquency during the Outcome Period.

V. Typical Characteristics Utilized

Typically, performance scoring models utilize the following types of information regarding past behavior to forecast future performance of a customer:

Delinquency during performance period

-highest, average, number of times delinquent

Account activity during performance period

-months with purchases

-months with statements

Account balance during performance period

-high, average

-recent changes in balance

-relation of balance to credit limit

Amount past due

Returned checks

Age of account

New applicant credit score

Although most performance scoring models have not employed credit report data in the past, the authors have been successful in utilizing the following data in performance scoring models that they have developed (where the credit report data have been combined with the creditor's own ledger experience, or have been used independently):

- Trade ratings
- Type of trade
- Inquiries
- Past due balances
- Derogatory information

An illustration of the variables included in a performance scoring model is shown in Exhibit 1. Note that the variables are derived both from the creditor's master file and a credit bureau.

VI. Methodology Used to Develop Performance Scoring

Discriminant analysis is the most common method used to develop new applicant scoring models. Typically, there are only two groups considered directly in the final model development: (1) creditworthy and (2) noncredit worthy applicants. Other techniques also have been utilized including heuristic searching procedures and mathematical programming.

The same procedures can be utilized to develop a performance-scoring model, particularly if the model is designed to predict membership in one of two groups. In many cases the two groups are those accounts that became more seriously delinquent versus those accounts that did not. In addition, n-group discriminant analysis can be used when the objective of the performance model is to predict membership in several different groups. In such cases the objective of the model may be to predict the likelihood of accounts currently in a given state of delinquency going to one of several different states of delinquency.

The performance scoring models presented in this study were developed using discriminant analysis. The Statistical Package for the Social Sciences [4] was used for data manipulation and model construction. actual results obtained for one model are presented in Section VII.

VII. Empirical Example

A. Setting and Sample

The results presented in this paper are based on empirical analysis of accounts in a bank credit card portfolio. The banker's objective was to determine if a performance scoring model could improve control of his revolving credit portfolio. The creditor used a new applicant scoring system to assist in the evaluation of new applicants and did not believe that there were any major problems in the new-account approval process.

Past performance data were obtained from the creditor's master loan record for several thousand accounts as of May 1980 (the "Observation Point"). The loan master file contained 12 months of previous account performance. Thus, the 12-month period preceding May became the "Performance Period." The payment performance of the sampled accounts was measured using the November master file. This six-month period (May to November) became the "Outcome Period."

EXHIBIT 1

A PERFORMANCE SCORING MODEL: AN ILLUSTRATION

Variable	Source*	Points
Two or more times delinquent in last 12 months	M	-107
One time delinquent in last 12 months	M	-52
Current dollar balance more than 10% over credit limit	M	-14
Average dollar balance in hundreds	M	-2 **
Number of months with purchases in last 12 months	M	3 **
Two or more unsatisfactory ratings	C	-30
One unsatisfactory rating	C	-18
Number of department store trade items	C	-12**
Two or more "too new to rate"	C	-10
Previous months dollar balance in hundreds	M	-3**
Credit limit in hundreds	M	3**
One or more "public record derogatory" ratings	C	-20
Three or less good ratings	C	-15
Payment or purchase activity in current month	M	18
Current balance greater than previous months balance	M	-18
Two or more finance company trade items	C	-5
Two or more slow ratings	C	-12
One slow rating	C	-5
Constant (All accounts receive these points)		180

*SOURCE: M = Creditor's master file, and C = Credit bureau files.

**These values are multiplied by the value of the variable to determine the points assigned to the variable. For example, if the average dollar balance in hundreds was 7, the points assigned to that variable would be $7 \times 2 = 14$.

The selection of the duration of the Past Performance Period (12 months) and the Outcome Period (six months) was somewhat arbitrary. However, the 12-month period is typical of the time period of past performance that creditors retain on their master files. Since the performance scoring model would be applied monthly to all existing accounts satisfying certain definitions, a relatively short Outcome Period seemed more appropriate than a long one.

Several stratified samples were selected, among them a sample of accounts that were one month delinquent at the Observation Point. This sample was divided into three groups: (1) accounts that became current and were never again delinquent for the next six months, (2) accounts that were no worse than one or two months delinquent for the next six months, and (3) accounts that became three or more months delinquent during the next six months. A discriminant model was constructed using only groups (1) and (3), but the resulting discriminant score was calculated for accounts in all three groups. Prior to construction of the model, the total sample was divided into an analysis sample and a validation sample.

B. The Model's Predictive Power

Exhibit 2 presents an illustration of the resulting performance scoring model. The points and variable definitions have been modified slightly to protect the proprietary nature of the actual model. The model includes data from the creditor's master file and from credit bureau files. Since analysis and validation sample results were nearly identical, this example of a practical application of the forecasts is based on the predicted performance of the entire sample (analysis and validation combined).

Example: Accelerated Collection Effort. This example will illustrate one application of the ability to forecast the future payment behavior of those customers that are one month delinquent. Assume the following information regarding a typical group of customers that are one month delinquent at a point in time (based on billing cycle):

- (a) The number of customers that are one month delinquent at the Observation Point (for example, at the time of billing) is 10,000.
- (b) The worst delinquency during the next six months will have the following pattern based on historical roll rates:

Never late	7140	(71.4%)
1 - 2 months late	2260	(22.6%)
3 or more months late	<u>600</u>	(6.0%)
	10000	

- (c) Suppose that it cannot be justified economically to begin collection activity (other than sending a polite reminder) on all 10,000 one-month delinquent customers. As observed earlier, normal roll rates may forecast accurately the number of one-month customers that will achieve higher delinquency (on the average), but they do not enable the collection manager to identify the specific customers most likely to become more delinquent. Thus, whatever collection strategy the creditor selected (including a decision to do nothing) must be applied to all 10,000 customers.

Based on overall portfolio roll rates, we are able to forecast that 6.0 percent (600 out of 10,000) of the customers that are one month delinquent will become three months or more delinquent and 22.6 percent (2,260 out of 10,000) will remain one-month or become two-months delinquent during the next six months.

However, assume that the creditor wishes to identify "high-risk" customers and employs performance scoring, with the results shown in Exhibit 2. First, let us consider all one-month customers scoring below 50. Out of a total of 2000 one-month delinquent customers (only 20.0 percent of all one-month delinquent customers), we observe that in the following six months 370 customers (18.5%) were never late, 1260 customers (63.0%) were one or two months delinquent, and 370 customers (18.5%) were three or more months delinquent. We have thus been able to identify 61.7 percent (370 out of 600) of the customers that will be three or more months delinquent during the next six months and 55.7 percent (1260 out of 2260) of the customers that will be one or two months delinquent during the next six months by focusing on only 20 percent (2000 out of 10,000) of all the customers that were one month delinquent.

Viewing the result in another way, let us compare the forecasting accuracy obtained by the performance scoring model on the 2000 customers with the accuracy that would be obtained on a random subset of 2000 customers using the known roll rates:

Six-Month Delinquency Outcome

	Total	Never Late	1 - 2 Months Late	3+ Months Late
Performance Model	2000	370 (18.5%)	1260 (63.0%)	370 (18.5%)
Random Selection	2000	1428 (71.4%)	452 (22.6%)	120(6.0%)

EXHIBIT 2
NUMBER OF CUSTOMERS ONE-MONTH DELINQUENT SCORING BELOW PERFORMANCE
SCORE BY FUTURE DELINQUENCY OUTCOME

Performance Score	Total	Never Late	1 - 2 Months Late	3+ Months Late
60	2700(27.0%)	750 (27.8%)	1500 (55.6%)	450 (16.7%)
50	2000 (20.0%)	370 (18.5)	1260 (63.0%)	370 (18.5%)
40	1500 (15.0%)	170 (11.3%)	1000 (66.7%)	330 (22.0%)
30	1200 (12.0%)	70 (5.83%)	850 (70.8%)	280 (23.3%)
20	850 (8.5%)	40 (4.7%)	560 (65.9%)	250 (29.4%)
10	500 (5.0%)	10 (2.0%)	320 (64.0%)	170 (34.0%)

We see that the performance-scoring model is able to forecast future behavior on the subset of 2000 customers much more accurately than the creditor would be able to do using only the historical roll rates. Consequently, the performance-scoring model is able to forecast future performance with sufficient accuracy to allow the creditor to focus an early collection effort on an easily manageable subset of the one-month delinquent customers.

Utilization of Credit Report Data Only. In order to use past ledger performance as an effective forecasting or control mechanism it is necessary that existing ledger experience be scored and updated on an automated (computerized) basis. Some creditors may not have sufficient computer hardware or software capability to provide automated scoring. The lack of ability to score on an automated basis does not necessarily mean that a creditor cannot make use of performance scoring.

The authors have utilized credit report data available at the Observation Point to forecast future customer performance. Although the accuracy obtained using credit report data alone is not as good as that obtained using ledger experience, the results are still very acceptable.

Consider Exhibit 3, where credit report data alone have been utilized to forecast the future delinquency of customers that were one month delinquent at the Observation Point. In order to compare the results with a performance scoring model utilizing ledger experience, we have used the same set of customers that were used in the previous example. The performance score intervals of the credit-report-only model have been selected to provide the same numbers of customers scoring below each interval as in the previous example. Thus, where 2700 accounts out of 10,000 scored below 60 in the example, 2700 customers out of 10,000 scored below 76 on the credit-report-only model. In Exhibit 3, we assume the same roll rates that were used for the previous example.

We will now compare the results obtained where 2000 of the 10,000 one-month delinquent customers score below the appropriate performance score (a score of 50 in the previous example and a score of 69 in the credit-report-only example). The delinquency outcomes of the two models are compared with the outcomes expected from random sample of 2000 customers.

EXHIBIT 3

NUMBER OF ONE-MONTH DELINQUENT CUSTOMERS SCORING BELOW PERFORMANCE SCORE BY FUTURE DELINQUENCY OUTCOME

Performance Score	Total	Never Late	1 - 2 Months Late	3+ Months Late
76	2700 (27.0%)	1143 (42.3%)	1162 (43.1%)	395 (14.6%)
69	2000 (20.0%)	728 (36.4%)	939 (46.9%)	333 (16.7%)
62	1500 (15.0%)	485 (32.3%)	735 (49.0%)	280 (18.7%)
58	1200 (12.0%)	365 (30.4%)	593 (49.4%)	242 (20.2%)
51	850(8.5%)	230 (27.1%)	427 (50.2%)	193 (22.7%)
38	500	104 (20.9%)	270 (53.9%)	126 (25.2%)

Six-Month Delinquency Outcome

	Total	Never Late	1 - 2 Months Late	3+ Months Late
Ledger model	2000	370 (18.5%)	1260 (63.0%)	370 (18.5%)
Credit-report only model	2000	728 (36.4%)	939 (46.9%)	333 (16.7%)
Random selection	2000	1428 (71.4%)	452 (22.6%)	120 (6.0%)

While the credit-report-only model is less accurate in identifying future delinquency problems, it still is much superior to random selection based on known roll rates.

A creditor that submits a monthly transmittal tape to a credit reporting agency could flag certain customers (for example, all one-month delinquent customers) to be scored by the reporting agency. The reporting agency could score the flagged customers at the same time that it is updating its own files and then pass the performance score back to the creditor either on all customers that were scored or on a subset designated by the creditor (for example, all customers scoring below 69).

VIII. Implementation

To insure successful implementation of a performance scoring model the design of the overall account management system as well as the impact on the organization caused by implementation of the system must be considered.

It is easy to calculate the performance score since the data are typically contained in the creditor's computerized master file and thus the scores can be generated by the computer without manual input. In spite of the calculation ease, several other implementation issues arise. More often than not, the accuracy of the scoring formulas themselves is not the most important factor in successful implementation of a performance scoring system. Generally, whether the implementation battle is won or lost is determined by far more fundamental concepts than the technology upon which the methodology of performance scoring is based. One factor that will significantly affect the successful implementation of the performance scoring system is the identification and specification of goals that are both measurable and realistic.

A second very important factor is the creditor's willingness to change its procedures (for example, with respect to collection prioritization or credit limit assignment and review). To gain the most from performance

scoring, a creditor must be receptive to change. One fact that stands out clearly in the literature written about management change is that change requires careful managerial planning. The importance of proper planning and proper system design to the successful implementation of the performance scoring system cannot be overstated.

The performance scoring model must be integrated within the overall credit granting and credit review process. This integration requires that existing and future technology be considered as well as the existing and future human resources. Every effort should be made to involve personnel from senior management all the way down to the actual user group. Commitment must be obtained at all levels to ensure successful implementation of the system.

IX. Monitoring Impact of the Models

Many creditors have had experience in monitoring the impact of new applicant scoring systems. They are able to determine how well the new applicant scoring system is working by comparing those results to historical forecasts and the actual results obtained during previous time periods. They typically measure the following items:

- (1) The score distribution of applicants
- (2) The delinquency of accounts by credit score
- (3) The delinquency and charge-off rate of the credit portfolio
- (4) The delinquency of judgmental overrides of the new applicant scoring model .

Items similar to those measured for new applicant scoring systems can be developed for performance scoring systems. However, there is an important difference in the utilization of a performance scoring system and a new applicant scoring system. The action taken as a result of the performance scores often will change the very relationships that exist in the model. Thus, a creditor must set up control groups, where no action or a different action is taken from that normally taken on the basis of the performance score . The results of the control group's performance can then be compared to the performance of the accounts for which different actions are taken in order to determine the model's ability to forecast future performance as well as the appropriateness of alternative actions that are taken.

X. Conclusions

Data from creditors' master account files, and from credit bureaus can be used to develop performance scoring systems that can predict future customer behavior far better than "roll rates," which forecast only average customer behavior. Such predictions of future payment performance enable credit grantors to improve decisions regarding collection efforts, credit line changes, purchase authorizations, and cross-selling efforts. As creditors both-reduce the cost and improve the efficiency of these credit decisions, both consumers and the credit grantors benefit.

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