# Implementing a competing limit increase challenger strategy to a retail-banking segment



**Derrick Nolan**

**108186852**

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Supervisor: Prof. P. D. Pretorius

VANDERBIJLPARK

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ABSTRACT

Today, many financial institutions extending credit rely on automated credit scorecard decision engines to drive credit strategies that are used to allocate (application scoring) and manage (behavioural scoring) credit limits. The accuracy and predictive power of these models are meticulously monitored, to ensure that they deliver the required separation between good (non-delinquent) accounts and bad (delinquent) accounts.

The strategies associated to the scores (champion strategies) produced using the scorecards, are monitored on a quarterly basis (minimum), ensuring that the limit allocated to a customer, with its associated risk, is still providing the lender with the best returns on their appetite for risk.

The strategy monitoring opportunity should be used to identify possible clusters of customers that are not producing the optimal returns for the lender. The identified existing strategy (champion) that does not return the desired output is challenged with an alternative strategy that may or may not result in better results. These clusters should have a relatively low credit risk ranking, be credit hungry, and have the capacity to service the debt.

This research project focuses on the management of (behavioural) strategies that manage the ongoing limit increases provided to current account holders. Utilising a combination of the behavioural scores and credit turnover, an optimal recommended or confidential limit is calculated for the customer. Once the new limits are calculated, a sample is randomly selected from the cluster of customers and tested in the operational environment.

With the implementation of the challenger, strategy should ensure that the intended change on the customer's limit is well received by the customers. Measures that can be used are risk, response, retention, and revenue. The champion and challenger strategies are monitored over a period until a victor (if there is one) can be identified.

It is expected that the challenger strategy should have a minimal impact on the customers affected by the experiment and that the bank should not experience greater credit risk from the increased limits. The profit from the challenger should increase the interest revenue earned from the increased limit. Once it has been established through monitoring whether

the champion or the challenger strategy has won, the winning strategy is rolled-out to the rest of the customers from the champion population.

# OPSOMMING

Die meerderheid finansiële instellings wat vandag krediet toestaan, maak gebruik van geoutomatiseerde kredietbeheerkaartbesluitnemingenjins om kredietstrategieë te aan te dryf wat krediet limiete toeken (aansoek punte telling) en beheer (gedrags punte telling).

Die akkuraatheid en voorspellings-sterkte van hierdie modelle word sorgvuldig dopgehou om te verseker dat dit die verwagte skeiding tussen goeie en slegte kliënterekeninge op verskillende vlakke lewer.

Die strategieë geassosieer met die attribute puntetellings (kampioen strategie) is ontwikkel deur gebruik te maak van telkaarte, en word op 'n kwartaallikse basis dopgehou ten einde te verseker dat die limiet wat aan die kliënt toegeken is, met die geassosieerde risiko gekoppel word, en dat die kredietverskaffer steeds die beste oplewering vir risiko ontvang.

Tydens strategiemonitering, word moontlike kliënttrosse geïdentifiseer wat nie vir die kredietverskaffer die optimale opbrengs lewer nie. Hierdie trosse moet 'n relatiewe lae kredietrisiko en vraag na krediet hê, maar steeds die kapasiteit hê om die skuld te betaal.

Deur gebruik te maak van 'n kombinasie van gedragspuntetellings en kredietvlakke, kan 'n optimale voorgestelde-/vertrouenslimiet bereken word vir die kliënt. Sodra die nuwe limiete bereken is, word 'n ewekansige seleksie gemaak van die tros kliënte en getoets in die operasionele omgewing.

Met die implementering van die uitdagerstrategie moet verseker word dat die voorgenome verandering op die kliënt se limiete goed deur die kliënte ontvang word.

Die monitering van die kampioen- en uitdagerstrategieë verskaf die strategiese bestuur met die mag om te identifiseer wie die wenner tussen die kampioen en uitdager is. Dus word beide die monster en die oorgeblewe totale groep gemonitor op 'n maandelikse basis vir 'n bepaalde tyd.

Daar word verwag dat die uitdagerstrategie so klein as moontlik impak op die kliënte in die eksperiment sal maak, en dat die bank nie blootgestel sal word aan groter kredietrisiko as

gevolg van die verhoogde limiete nie. Die wins van die uitdager behoort die rente-inkomste verdien deur die verhoogde limiete, te verhoog.

Sodra daar tydens die moniteringsfase vasgestel is watter een van die kampioen- of die uitdagerstrategieë gewen het, sal die wenstrategie op die res van die kliënte in die kampioen populasie toegepas word.

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# CHAPTER 1: Introduction

Automated scoring was introduced in South African banks in the mid- to late 1990s. Most of the institutions implemented bespoke (models based on industry experts and general trend estimated) models. Rudimentary strategies were developed for the bespoke model scores. Since most automated scoring systems are provided by an external vendor to the lender, installation and maintenance of these was offered as a packaged deal. Automated decision making was and still is a very expensive practice; fortunately, the benefits far outweigh the costs.

Lenders now see the benefit of using an automated decision system in providing credit to borrowers. The challenge, however, is maintaining the system. Recently, it has become more evident that lenders are developing their own scorecards internally (Siddiqi, 2006:2). The benefits of this are listed by Siddiqi (2006:2,), which include:

- An internal developer has direct contact with the business and product, contributing to an enhanced understanding of the lenders and their representative credit and systems data.
- An advantage of understanding the environment (credit, system, and product) better is the speed and accuracy of developing models.
- The cost is lower since internal resources are used instead of consultants.

In order to implement a rating system, the following have to be available:

- Credit related data;
- Automated scoring systems;
- Staff with the skills and knowledge of scorecard/rating system development and implementation;
- Credit scoring technology (Anderson, 2007:6)

An automated score would add no value if strategies do not support the decision making, converting the score to a useable decision. This research project focuses on these strategies, in particular on methods for identifying opportunities based on tracking reports, then devising strategies that can be optimised in a controlled and measured environment.

There are various areas in which scoring technologies are applied, which are discussed in Section 1.1.4, some of which are:

- account origination—otherwise known as application scoring;
- account management—otherwise known as behavioural scoring;
- account debt collection—otherwise known as collection scoring;
- debt recovery—otherwise known as payment projection scorecards; and
- propensity and attrition modelling—otherwise known as churn models

The research project is focused on the second area, behavioural scoring, and the optimisation of the strategies associated to a specific product, namely cheque accounts. Behavioural scoring is used in lending products to manage the increase and decrease of limits assigned to the account, based on the account's credit risk score and associated strategy.

In this chapter, the problem is contextualised in Section 1.1, and the problem statement is described in Section 1.2. Thereafter, the aspects of banking that will be affected are addressed in Section 1.3. Next, the importance of this research project is posited in Section 1.4. Then, the retail-banking environment is described in Section 1.5. In Section 1.6, the research questions and aims are presented. Following this, the benefits of implementing a champion–challenger are given in Section 1.7. Thereafter, the research methodology is briefly outlined in Section 1.8, and finally, the chapter outline is provided in Section 1.9.

## 1.1 Contextualisation of the problem

### 1.1.1 *Illustration of banking credit life cycle*

The typical credit life cycle consists of the following components:

Non-credit products – typically a known as a savings account with no credit limit attached to the facility. Full banking facilities are available to clients, such as branch transactions, electronic transfers, and debit orders. If the account holder attempts to withdraw money from the account less than zero, the payment is dishonoured by the bank. If this customer is considered as a potentially good customer, one could use external measures (credit bureau) to provide the customer with product with a credit limit, described below.

Transactional unsecured products – credit cards, current accounts, and personal loans are typically viewed as unsecured facilities for personal banking customers, since no underlying collateral or security is associated to the credit limit. In small to large businesses it is common practise to demand some form of financial security for the facility.

Secured products – vehicle and asset based finance and home loans are typically seen as secured products, since the asset or the property can be seen as security. There is usually very little behaviour on the account, since the customer has a monthly instalment, thus obligated to transact once a month until the full amount is settled. The agreement between the bank and the customer is to sell the asset or property if the customer can no longer afford the repayments, thereby settling the outstanding debt.

The banking credit life cycle is best explained by means of an illustration:

A mother walks into a branch with her son, to open his first bank account. In order to introduce him to banking, his monthly allowance is paid into the account. He keenly saves his money each month, to buy the radio-controlled car he so dearly wants.

After completing his schooling, the son decides to go and study, for which he has to obtain a student loan. Because his mother helped him open an account, he is not a stranger to banking, and the bank provides him with the loan on provision that his parents sign surety for the loan. While he completes his degree, his parents service the interest portion of the loan every month.

After completing his degree, he starts his first job, and he needs to provide his employer with a bank account number into which his earnings can be paid. With his earnings, he pays off his student loan, and starts saving for a deposit for a place of his own. His salary is deposited into his account every month, and money is withdrawn when he needs to pay for living expenses and entertainment. Soon he is approached by the bank with a credit card. The credit card limit is based on his salary, as paid into the account every month.

The car given to him by his parents is costing more to maintain and is becoming unreliable. He thus wants to replace it with a new, affordable, and reliable vehicle. He shops around for the right car, and sells the old car. He now needs financing for the new car, approaches his bank, and applies for a loan to buy a car. The bank then agrees to finance the vehicle.

The above example attempts to highlight the progression in the credit scoring lifecycle. The first product the son had was a non-credit product, followed by a student loan, a credit product with special terms in which only the interest portion is to be serviced month on month, until the son is capable of paying the full instalment. The son moved from a traditional savings account to a transactional savings account when his salary is deposited and debit orders are linked to the account. At this point, the bank could offer the customer a current account with an overdraft facility.

With the use of attrition models, banks identify opportunities to sell more products to customers, thus offering the customer a credit card in the example is a result of such modelling and associated strategy.

Once a credit product has been granted to a customer, the transactional credit behaviour of the customer on the account is recorded daily. Based on the customers behaviour and credit turnover limits are calculated in the background. According to these limits and behaviour, product offers are made to customers, in this case a credit card. The son approached the bank for loan to purchase a vehicle, showing the different tipe of application scorecaring taking place. The credit card was offered to the son by the bank (solicitation) and the vehicle is by request.

Fortunately the son kept paying his bills, thus avoiding the last cycle in the lifecycle namely collection scoring.

### 1.1.2 Changes experienced in banking credit life cycle

<u>The customer</u>

As customers progress through the credit life cycle, their needs change. Credit lending is faced with continuous change, not only in terms of product requirements, but also in terms of credit provision (such as managing limits and granting facilities. It is thus imperative that the right type of credit products is provided: the right size of facility at the right time to the right people.

In the example in given above, the customer has progressed through various phases in life, and has experienced changes in banking needs and practices as well. The customer's banking needs have progressed from a savings account to a student loan, to vehicle finance and a credit card.

<u>The bank</u>

In order to cope with the rapid change faced not only in technology, but in managing credit risk portfolio in general, a lending institution has to continually improve methodologies, technologies, and strategies, among others.

Models are automated in a decision engine, which

- automatically gathers all the necessary data elements required to calculate a credit risk score;
- automatically calculates a credit risk score;
- produces a stored record of the decision; and
- calculates strategies assigned to the score, using the stored decision record, for example, the decision to accept or decline an application based on a cut-off in application scoring.

### 1.1.3 Current practice of a credit provider

The credit provider in this research project reviews the limits on cheque accounts only once a year. As behaviour scoring has only been in use for a few years, the account strategies are still very conservative, and trust in the calculated limits is not yet established. There is no formal environment and process established, in and through which to identify, implement, and test new strategies (termed *challengers – the newly formulated strategy*) against existing strategy (termed *the champion*, as it is the strategy that is implemented).

An approach to keeping up with change is that of continuous improvement. Continuous improvement is widely used by manufacturers' quality management departments, to improve manufacturing processes and reap great reward. Applying continuous improvement to account management will help lenders to cope with ever-changing conditions. In this research project, the focus is on the continuous change in the customer's credit needs and the controls and systems that govern this relationship.

Banking is a relationship, governed by legislation, between a customer and a financial service provider. One of these is the Basel II Accord, which is intended to regulate the amount of capital a bank carries in relation to the risk of its exposure (Gup, 2004). Credit scoring is one of methodologies suggested by the accord, to manage and determine the risk of an exposure to the bank. Strategies are the vehicle used by banks to manage the numerical score into a clear business decisions based on business accepted bad rates and risk appetite.

If a bank has a behavioural scoring system in place with strategies, to manage the respective scored populations, what do they need to do to ensure that the strategies are up to date, apart from redeveloping a scorecard or adjusting its factors? How should they identify opportunities, to improve the quality of the credit risk book, deriving the greatest profit from the customer without being careless in terms of risk and exposure? What should be done with identified opportunities? How can the strategies be challenged, to see whether any market change has had an effect on the population? These questions can all be addressed and resolved with a champion–challenger.

A credit scoring survey of banks in the southern hemisphere (Australia, New Zealand and South Africa) was undertaken in 2000 for Deliotte New Zealand, which shows that only one bank in the survey committed to employing champion–challenger strategies (Perry, 2002).

The question after implementation of controls and systems through automated systems is: are there opportunities for optimising the relationship of risk and profit with a customer, without adversely affecting the relationship with the customer?

In this study, we search for such opportunities to optimise the relationship of risk and profit with a customer.

### 1.1.4 The credit cycle

McNab and Wynn (2003:3) present the credit cycle as follows:

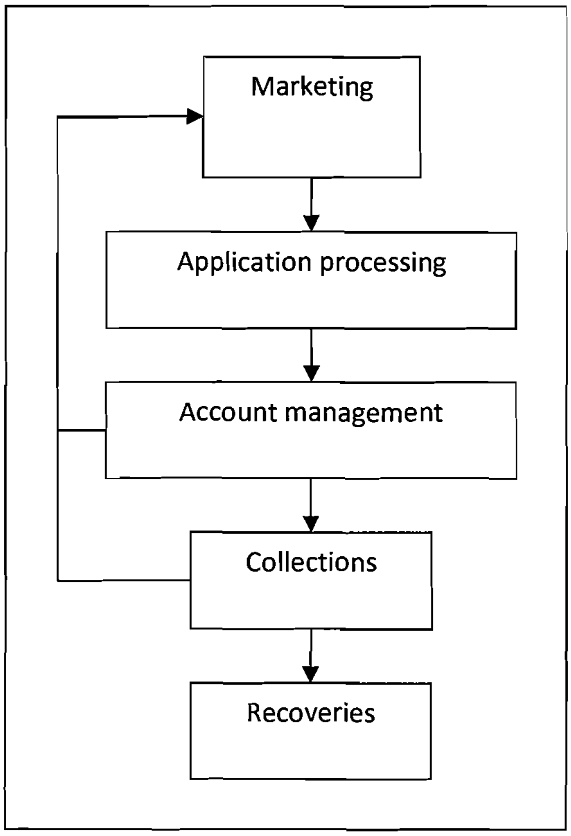


Figure 1: Credit cycle

In this section, the credit life cycle as shown in Figure 1 above is discussed along with the associated modelling tools.

<u>Attrition model</u>

Attrition models are built on existing customers of a lending institution. Attrition is the ability of a lending institution to broaden the number and types of products to a customer (*Marketing* in Figure 1). From the illustrative example given in Section 1.1.1, the student loan or savings account information indicated that there is a credit turnover every month into the account, thus upping the attrition score, and thereby qualifying the customer for a possible credit product, in this case a credit card. Furthermore, a response score can calculate the probability of a customer responding to the offered product or new credit limit.

Account origination: application scoring models

Account origination (*Application processing* in Figure 1) credit decisions are based on a model termed an application scorecard. All credit-related products are scored at application. Upon generating an application score, whether the application should be approved or declined is determined through a cut-off. A cut-off is the mechanism used to approve or decline a loan, for example, a score above 600 indicates an approval, while a score below 600, indicates that the loan should be declined. This mechanism is referred to as a strategy. If the loan's credit is acceptable to the lender, it is approved. The interest rate at which the loan is to be priced is calculated using a pricing strategy. Typically, a pricing strategy is based on the risk associated with the loan and the profitability of the loan. Other factors are taken into consideration as well, for instance, the credit behaviour of the customer on other loans at the institution. In addition, the portion of the customer's overall credit limit that is to be allocated to the required loan is determined, these strategies are referred to as limit strategies.

Account management: behavioural scoring models

"A behaviour score predicts the likelihood of an account going 'bad' based on payment history, usage, delinquency and timing characteristics. The behaviour score is calculated on a monthly basis and is therefore always up to date, accurate and reflects the customer's current risk" (Dekker, 2004).

A behavioural scorecard is developed on credit and account behaviour over a period (observation and outcome period of at least one economic cycle), to predict the probability of default for a year's time. The credit-scoring paradigm automates the process of selecting credit applicants or existing credit holders into two basic categories, namely good and bad, in a faster, cheaper, and better manner than historical judgemental assessment (Joseph, 2001:4).

On a monthly basis, the customers either service or do not service their debt. There is a clear distinction in the handling of two different categories of loans, namely those with underlying security (vehicle and asset-based finance or home loans) and those without underlying security (cheque account, personal loans, and credit cards). The payment behaviour in the two categories is distinctly different. A vehicle or a home loan will only be serviced once a month, unless it is an access bond where the lender is allowed to draw down on the available capital accumulated in the bond, while with cheque, credit cards, and personal loans, the lender can access the funds on a daily basis, and deposit money at any time during the month, although it is usually required that the debt is serviced once a month by a lender. These payments or absence thereof, or the overdrawing of facility limits is account behaviour (*Account management* in Figure 1). Typically, accounts that are not serviced or that have degrees of servicing are considered bad.

Based on behavioural scores, payments above limits are either declined or paid, greater limits are granted or declined, and other accounts are offered or not. All these actions are strategies associated to the scores or score bands.

Debt management: collection scorecards

Once an account is not serviced, the account holder is indebted to the lending institution for the outstanding balance. Collection scorecards are used to manage accounts that are considered in debt. Collection scorecards can be used to model a number of outcomes:

- the probability of an account holder settling the outstanding balance;
- the possible value that can be recovered from the outstanding balance;
- the probability of a account holder missing another payment.

Based on the score produced from the scorecard and the associated strategy, a customer is either sent a text message (Short Message Service—SMS) or fax, telephoned, or in high risk cases, mailed a letter of demand.

Debt recovery: payment projection scorecards

Once the customer has been thought the debt management cycle, and there has been no success, the lender will have a predetermined point at which to sever the relationship with the customer. The customer will then no longer be considered a customer of the lender, and the focus of recovery will then be to settle the outstanding debt in the most efficient way (McNab & Wynn, 2003:3).

In Section 1.2, the problem statement is described.

## 1.2 Problem statement

A credit scorecard provides a risk score indicating the likelihood of a customer defaulting in the next year, which is useless to the bank without strategies supporting the credit decisions to be made. The process of deriving an action from the risk score is termed credit risk strategy management, which is also referred to as credit risk management (McNab & Wynn, 2003:3). An example of this would be a cut-off score on an application scorecard, where customers with a score above this will be accepted, and those with a score below the cut-off will be declined.

Scorecards usually have a two- to three-year validity period. When the scorecard is implemented, it is already out of date, although still valid when it is recalibrated. The scorecard is built on historical data, with the development life cycle for a scorecard approximately six months. During this time, the scorecard is recalibrated in terms of characteristics, and optimised for providing the best end results, which is good judgment in terms of good and bad customers, and assigning the best strategy based on the score. A behavioural scoring system is checked every quarter for validity. Over time, the validity of the scorecard deteriorates as internal and external changes take place, causing the scored population to shift.

Redeveloping a scorecard generally takes approximately six months, with an additional month required to make the proposed changes to the strategy, and another month required for change control, resulting in an overall eight months, if the process was successful. If, in the quarterly review, a population shift on a particular strategy was identified, for example, the interest rate was lowered resulting in customers having more to spend, or a number of interest rate hikes had taken place resulting in customers defaulting, then the current strategy can be challenged with a competing strategy. In both scenarios, a better-suited strategy would benefit the customer and the bank.

The problem is thus to continually challenge the applied strategies with better-suited strategies, resulting in more profitable yet happier customers.

The next section addresses aspects of banking that will be affected.

## 1.3 The aspects of banking that will be affected by the experiment

Mainly retail banking is going to be affected, as opposed to corporate banking, as this is the segment of the bank's portfolio on which the credit department focuses. The subsection of retail banking to be affected is that of retail-banking credit.

### 1.3.1 Retail banking

The customers that are serviced by retail banking define retail banking, namely a person and not a company. Because there are so many more individuals than companies, sufficient numbers are available, thus the modelling can be conducted more easily.

According to Howard (2003:4), a champion–challenger strategy implemented on a retail customer base increased the profitability of low risk clients, and did not affect the bad debt levels.

The objective of the retail division of a bank is to be the best place to bank, in terms of service and facilities, and the best place to work, in terms of employee work satisfaction. By ensuring that the retail division of a bank provides the most efficient service possible to the client, the bank is brought a step closer to attaining its goal.

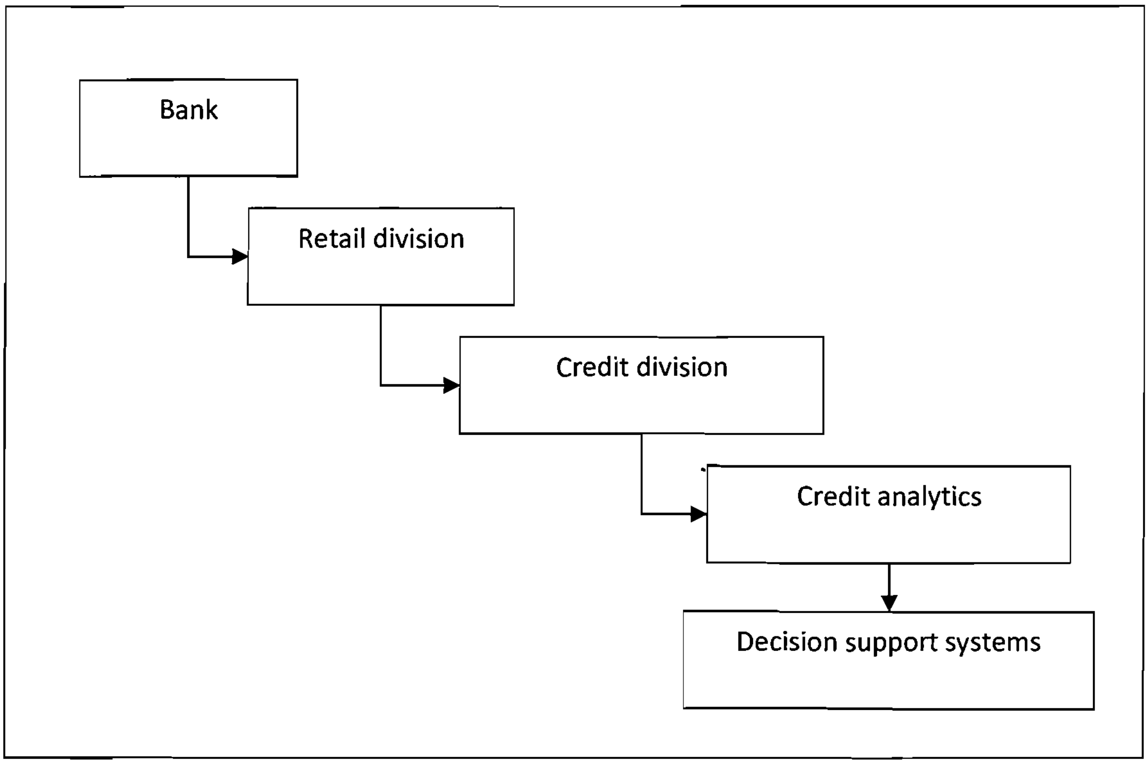


Figure 2: Hierarchical benefits

As can be seen in Figure 2 above, the profit benefit flows into the organisation, and as discussed above, the financial establishment provides its services to customers.

### 1.3.2 Data sources

Behavioural scoring systems are used to determine the risk scores pertaining to the creditability of a customer. The behavioural scoring system is a program that automatically runs on a monthly basis, as the information upon which decisions are based is required monthly. The system is located on the mainframe and uses behavioural information from more than one transactional system located on the mainframe, for example, a current account system. Complexity is initiated here as the mainframe environment is under stringent change controls. Interactions between systems have to be problem free as the other automated services are provided on a transactional level, which is utilised by branches and customers online (internet banking).

The automated decision engine automatically collates data from product systems and archived decision information, in order to score the customer. Archived score and behavioural information is used to create summary fields, which will indicate the severity or zealousness of the customer's behaviour.

In order to develop or analyse a credit portfolio, a compilation of various kinds of data indicating a fair amount of history is required. According to McNab and Wynn (2003:17) the quality of data is reliant on consistency and accuracy. The consistency of data can be measured by the number of fields that have not been captured on an application form, as reflected in the application scoring history file. The accuracy of the data can be measured with shift indices.

### 1.3.3 Compliance

Bank for international settlements (BIS) is a bank that promotes cooperation between central banks and other institutions that aspire to monitory and financial stability (McNab & Wynn, 2003:274). The Basel committee on banking supervision introduced a capital accord in 1988. In 1999, a new capital accord was defined, which should be implemented by 2008 across the world. Specific attention is to be paid to internal discipline, particularly for banks who are aiming for internal ratings based (IRB) status. With IRB status, a bank can calculate its capital based on internal measurements for probability of default, exposure at default, and loss given default used to calculate the expected loss for which capital is carried. For the bank, there is an incentive to monitor their scorecards, as it highlights opportunities for increased profitability and the opportunity to carry less capital.

In the following section, the importance of this research project is posited.

## 1.4 The importance of the research project

As populations shift and operating and economic conditions change over time, the account base will react and behave differently in response to risk management strategies. The objective of risk management strategies is to alter account holders' behaviour over time, as such it is critically important that the strategies deployed by retail credit establishments continue to reflect the altered behaviour of the customer base. Champion–challenger testing is a process in which alternative strategies are tested in a controlled manner within the 'live' environment. Therefore, to ensure that the credit strategies are performing optimally, providing the best credit decision concerning their portfolio, and resulting in financial benefit to the bank, the champion strategies should be challenged continuously. Additionally, it is important to identify customers who are the most profitable to the bank.

In South African banking history, this research project is the first to attempt strategy-challenging methodology with their customers, giving them the advantage of being the first to benefit from this approach as will be demonstrated later in this dissertation. The end goal of the testing is to manipulate risk to such an extent that the bank is not negatively affected in terms of loss caused by risk and providing revenue through the utilisation of 'safe' revenue, and ultimately achieving client satisfaction from the adequate facility, and not the customer being reprimanded by the bank for over-utilisation of their limits.

Since credit scores, specifically in this case behavioural scores, are used to aid the decision to increase, decrease, or retain the limit. Deciding on the amount by which to increase or decrease the limit is based on contribution that is made by the customer towards the overall profit from the account.

An increasing number of banks are using contribution analysis to enhance the limit allocation decision, by using a combination of the credit score and the account holders' contribution (McNab & Wynn, 2003:80). In terms of a current account, these decisions are made daily for customers who exceed their limits. Based on the credit score, the customer is allowed or declined the option to spend more than the allocated credit limit. Historically, these decisions were done by hand in branches, thus taking up much time for the borrower.

Furthermore, cross-selling (identifying opportunities to sell other products to an existing customer) was predominantly undertaken by the marketing division based on the results from previous marketing information, without considering the credit risk associated to the offer (Neves, 2006).

According to Anderson (2007:39), statistical scoring was developed in 1936 when statistician Sir Ronald Aylmer Fischer published an article on the use of linear discriminate analysis. The methodology was used to classify different types of irises by using measurements from the plants. In 1941, David Durand applied the same technique, to classify good and bad businesses in terms of credit. The first noted scorecards were those of Henry Wells from the Spiegel Corporation and E. F. Worderlic of the Household Finance Corporation (Anderson, R. 2007:39).

In 1956, Bill Fair and Earl Isaac established the Fair Isaac Corporation. They implemented an application scorecard for American Investments, and towing to the success of the scorecard, it was embedded into American Investments' decision process. The process of scoring was further simplified by the use of computers, and lenders begun centralising their credit assessment operations.

Although automated systems are available on the market for optimising customers' limits, by using more than just the risk score and the contribution of a customer, there are still ways through which low-risk, high-response customers can be identified and targeted for a better profit for the bank. This research project aims to prove that even with limited automation it is still possible to optimise the profit from an identified population(Fishelson-Holstein, 2002:6), improving a limit-increase marketing campaign.

The retail-banking environment is described in the next section.

## 1.5 The retail-banking environment

The retail bank in this research project offers the following services:

- current accounts;
- credit cards;
- asset-based or vehicle finance;
- personal loans;
- investments;
- home loans; and
- savings accounts.

Current accounts are high risk as they are transactional products, and the facility is readily available to the customer with touch points, such as ATMs and point of sale devices. It is possible for a customer to withdraw funds up to the limit allocated to the account. In order to determine the decision of the level of a limit assigned to a particular type of customer, behavioural scoring was implemented 1999. The behavioural scoring system utilises risk and account-related information, to assign a risk score to a customer. Other products are behaviourally scored as well, but only credit-related products are depicted in Figure 3.

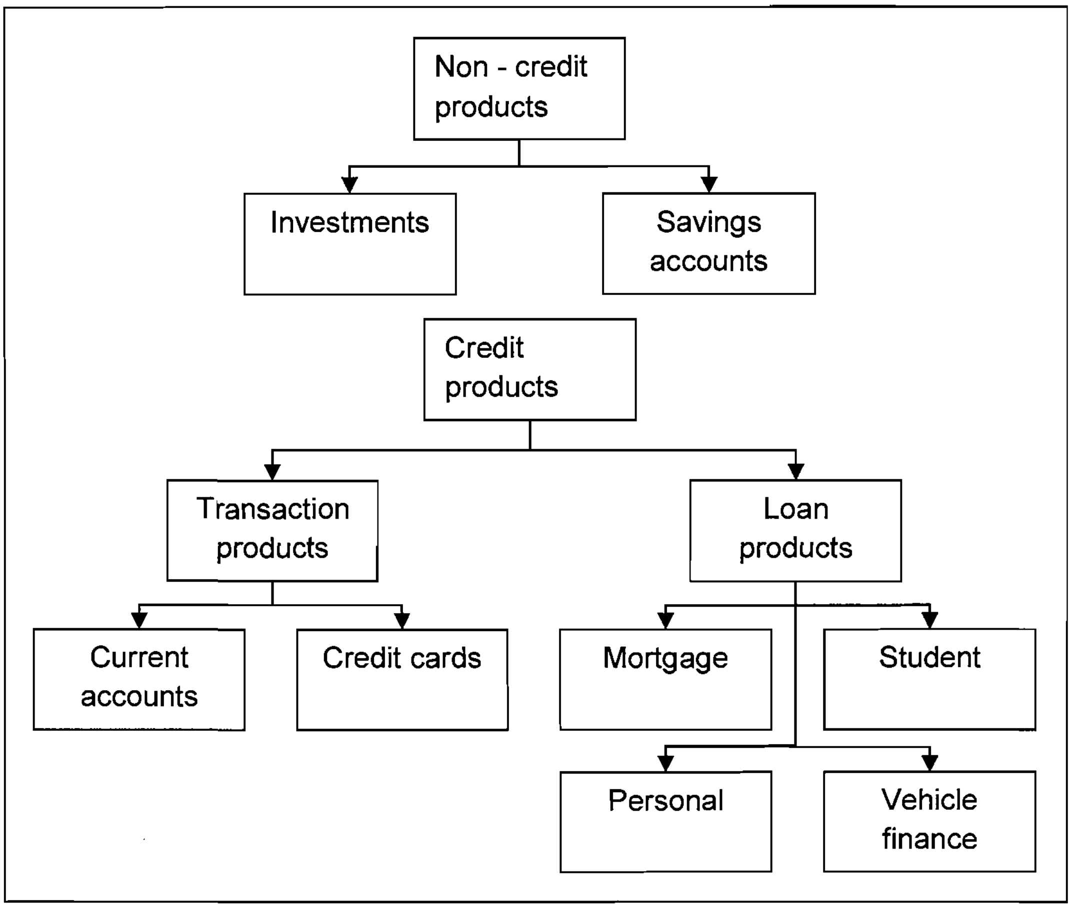


Figure 3: Banking products

Section 1.6 presents the research questions and aims.

## 1.6 Research questions and aims

Behavioural scorecards are used by banks and other financial lending institutions to credit score customers on a monthly basis. The more accurate/valid the model the more accurate the decision based on the score (strategy). The question thus is whether or not opportunities can be identified to optimise these decisions made on a monthly basis.

A bank has many product offerings to customer which product will the study focus on? The strategy that the study focuses on is the limits that are assigned to current account overdraft facilities. These limits are based on the monthly behavioural score and are usually only updated on an annual basis, unless some drastic measures have to be taken.

How does one identify opportunities for implementing limit increase champion-challengers? The only way to identify opportunities for possible optimisation, is to monitor the scorecards and the associated strategies on a regular basis.

The three main factors that contribute to the validity of a scorecard and the related strategies are:

- scorecard validity (outdated before it is implemented);
- scorecard redevelopment timeframe; and
- population shifts.

The aim of study is to:

- Provide examples from literature where champion – challengers have been identified and tested; and
- Identify a segment (sample thereof) of the population, based on their limit excess behaviour and facility (overdraft) utilisation and implement a proposed limit based on the risk score of the customer, challenging the existing limit on the customer's account.

### 1.6.1 Scorecard validity

Because a scorecard is built on historical data and the redevelopment thereof takes time, the implemented scorecard is only valid for a certain timeframe. If a banking population had no economic or market shifts, the scorecard would obviously be valid for a longer period, but because these environments are not static, a population shift can occur. The obvious solution to a changing environment is to change the intervals of redevelopment. The problem with this is that there are substantial costs involved in redevelopment, and once again, time plays a negative role.

### 1.6.2 Scorecard redevelopment timeframe

Complexity is initiated here as the mainframe environment is under stringent change controls. Interactions between systems have to be problem free as the other automated services are provided on transactional level, which is utilised by branches and customers online.

### 1.6.3 Population shifts

As explained above a scorecard would be valid for a longer period, if the environment that it functions in remains static. The reality, however, shows that there is change in all environments. Economic, market, and client behaviour environments play a role.

Economic environment

Considering the South African economic market of 2002, there were four increments in interest rates during the year. Changes such as these impact on a bank in terms of credit, as the population is influenced through increase rates, resulting in them having less money with which to pay outstanding payments.

Market environment

An example of market changes in banking is better offers from other banks, as every bank has its own risk appetite. These appetites drive the product and margin offers extended to portions of the banking market.

Client behaviour environment

Client behaviour changes for various reasons. For example, a client receives an increase in remuneration and thus has more money to spend. The inverse is demonstrated when clients lose their jobs through companies downsizing or adverse behaviour on their side.

The benefits of implementing a champion–challenger are given in the next section.

## 1.7 Benefits of implementing a champion-challenger

The benefits of implementing a champion–challenger can be derived from the environments in which the current system is functioning. The environments referred to here are not only the credit life cycle and systems development life cycle of the scorecard development and redevelopment, but also the economic and marketing conditions of the country. All these conditions influence the behaviour of customers, in terms of their risk appetite; this in turn influences their credit utilisation, and the customer's payment behaviour changes.

Because of the time associated with the development and redevelopment of the scorecards, the benefits of developing a credit limit strategy challenger are the time and ease of model implementation. The system change for the strategy has a lesser amount of risk impact and is a smaller change to be managed than a scorecard system change.

Market conditions are determined by different offers from competitors and the opportunity to provide a good product. It is important to have the ability to release a product in the market at an opportune time. Because of the delay in delivering a scorecard, it will already be outdated by the time it is introduced to the market. Considering the last statement, it is imperative to have a faster and more robust approach to developing a scorecard. Because the credit limit increase is a variable change, it proves to be a small manageable change.

Economic conditions cause the banking population to shift positively or negatively, giving the population either more to spend or less to spend. These factors directly change the spending patterns of the customers, and invariably influence the debt ratio. In order to manage these changes new strategies have to be modelled and implemented, which will allow banks to gain the maximum amount of income from the customers, while ensuring the customers needs are met. As with the other conditions as mentioned above, it is far better to change the strategy than the whole system. Implementing changes to the strategies will improve the validity of the scorecard, but will not replace the normal life cycle of the scorecard. Without credit limit increase strategy changes, the scorecard will remain valid for the intended time, but it will not optimise the possible increase in revenue should any of the above-mentioned conditions change. According to the Fair Isaac Corporation (Fair Isaac, 2003), an increase in the bottom line figure of 5% to 35% can be expected with the implementation of optimal credit line strategies.

### 1.7.1 Scorecard development benefits

"The predictive power of scorecards gradually deteriorates over the course of time, so that their performance needs to be monitored" (Hand, D. 2003). Possible reasons for this deterioration can be attributed to adverse economic changes that have taken place, for example, the interest rate was increased, causing people who are over-committed to default. Other economic changes including unemployment, gross domestic product, house price growth rates, and interest rates are valid reasons for redeveloping a scorecard. However, building a scorecard in good economic conditions should not affect its performance, as scorecards are relatively robust and should not be influenced by minor changes in the economy (Anderson, 2007:86).

Since the implementation of the model in he late 1990's the market environment has changed, other banks are offering facilities to the same customers at a better rate, causing customers to open facilities at other lenders, while their facilities granted with the original financial establishment lies inactive. Marketing strategies and competitor offers define the type of customer that an institution has. Changes in these strategies change the composition of the company's customer type. According to Anderson (2007:86), marketing strategies are aimed at one or more of the following:

- product: features of a product may be increased or decreased;
- pricing: lower interest rate, longer repayment terms, less service and penalty fees;
- promotion: different target markets and the type of advertising media;
- place: loci of advertisements; and
- distribution: the faster the marketing material reaches the intended segment the better.

Changes to any of the above causes unintended affects on the populations' credit risk. Owing to this, regular interaction between credit and marketing should take place.

From a credit perspective, Anderson (2007:87) suggests that the following factors should be taken into consideration when periodically reviewing a customer base:

- affordability: can the customer afford the debt?
- access to credit: lower-risk customers are approached by other lenders due to their good credit nature
- price sensitivity: higher-risk customers are not as sensitive to price as good customers are.
- financial sophistication: does the customer know how to handle debt?
- community and parental support: is there someone who can help with the repayment of the debt in a crisis?
- repayment mechanism: a debit order is most commonly used, but is the lending institution guaranteed repayment?
- contact ability: can the customer be contacted when a repayment was missed or for marketing campaigns?

As time progresses, technology improves and systems are updated. When these changes take place, it often happens that data from the old system is wrongly mapped to the new system, causing fields to reflect differently than expected, and thereby scoring customers differently. New data will be available internally or externally when, for example, a bureau has acquired another source of information or a merger has taken place bringing with it more customers and some overlapping customers.

Change in the scored population, can be caused by the population itself. Due to human nature, people would want to change if a better lending opportunity is presented. It is very difficult to quantify this attribute of human nature. Possible causes can be too many campaigns targeted at the customer or too few or the type of action that was taken when the customer defaulted for the first or umpteenth time. The reputation of a bank may have been tarnished by an adverse effect, or commitment to some charity or sporting event influenced people to change banks.

Stagnating scorecards

When a scorecard is monitored, and the results show that the scorecard is still very predictive and has not deteriorated significantly from a previously measured period, it is usually left in production. It is possible that the scorecard stays predictive with marginal decline in its power for an extended time (five years or more). After a period, the scorecard should be redeveloped, not to necessarily increase the strength, but to make the scorecard relevant again. For this reason, neural network scorecards are used in predicting fraud, which is updated monthly, as new fraudulent tactics are used when older ones have been identified.

Because of the above-mentioned factors, it is advantageous for a scorecard to be redeveloped once predefined criteria (triggers) have been breached, which can include a cut-off for relevance.

Adaptability to the credit life cycle of a customer, a customer could move between segments specified in a scorecard, for example, a common segmentation is a current account split for borrower, non-borrower segments, or in fixed-term loans or segmentation based on customers with a current account and those without those without. These population sizes should be measured as well when cross sell campaigns have been run, to ensure that a significant portion of the population still utilises a segment of a scorecard.

It is thus very important when developing a scorecard to state the measurements and the tolerances associated to these measures (for example a shift in the population greater than 10%), but even if this has been done, a great deal of care is to be taken when changes in any of the above-mentioned areas are identified.

In short, the benefit of redeveloping a scorecard is that it keeps the scorecard relevant to the current population, it keeps the scorecard accurate when changes occur, and it helps with decisions outside of the credit area, for example, the marketing department.

### 1.7.2 Benefits to retail banking

The benefit to a lender could be measured in terms of the way that it makes its profit. Lenders derive their profit from the amount of interest they charge. Only a margin of the interest they charge is seen as profit, since banks have a cost of capital, which they source from either the reserve bank or depositors. It is thus crucial for a bank's survival to lend to the right people (those with lower risk) at the right price.

A further benefit from lending the right amount to the right people is customer satisfaction. Ensuring that a customer can afford the debt and pricing the debt at the right margin provides the lender with a satisfied customer and a measure of assurance that the customer will be able to repay the debt, if something unforeseen should happen. The majority of lending institutions are focused on customer satisfaction and service as their differentiator from other lenders.

Owing to the low interest rate environment in Europe, the net interest margins across European banks dropped from €2.09 in 1994 to €1.46 in 2000 (McNab & Wynn, 2003:3). Thus, banks in that period pushed for high volumes of accounts, to make up for the squeeze on the margin then, even though the margin is small, many small margins should add up to a greater yield in profit.

Banks reduce the risk that they take on by implementing decision engines and using statistical techniques, to develop scorecards. The scores produced by the decision engines are then used in strategies to make decisions regarding lending to customers, for example, cut-offs and limit management. Banks use marketing campaigns, to enlarge their sway in the market. The more customers a lender has, the more competitively it can price its loans. The more products a customer has with one institution, the greater the reward in terms of transactions, interest, and fees. The marketing decisions are based on cluster analysis and other techniques from previous responses to marketing campaigns. Furthermore, banks have finance areas that determine the profit and losses incurred every month, and business decisions are made from the management information produced for each portfolio and product. Forecasts are made from these numbers, to support the decisions made for future lending

Combining the output from the marketing area with the credit scoring output in an optimisation will greatly enhance the decisions made by these areas, since there will be a consolidated view of the customer. This will further enhance the communication between these areas as well, events can be coordinated more effectively, and the impact managed from actions taken by either of the areas.

The research methodology is briefly delineated in Section 1.8.

## 1.8 Research methodology

The research in this paper focuses on credit strategies associated with credit scores, thus a tool to manage customer's credit behaviour. The behaviour of a customer is measured on a monthly basis with the help of behavioural scoring (account management), and customer behaviour is rewarded or penalised based on this behavioural score. Since the score is very granular they are broken up into deciles and a strategy is developed. The strategy experimentation methodology to be followed in the study includes the following steps:

- strategy design;
- strategy implementation;
- strategy re-evaluation; and
- strategy re-deployment.

Chapter 2 provides more detail about the research methodology.

In the last section, the chapter outline is presented.

## 1.9 Chapter outline

Chapter 2 will focus on the research methodology followed in the research and describe the phases associated to each step.

Chapter 3 will discuss in detail the analysis of identifying and choosing a champion and worthy challenger strategy. Scorecard monitoring reports and the measures contained within will be described in detail in this chapter.

Chapter 4 will detail the testing of the two competing strategies. To establish which one of the two strategies, the current strategy (champion) or the newly calculated (challenger) strategy.

Chapter 5 will describe how to approach the implementation phase, when the challenger strategy is found to be the most successful.

Chapter 6 will provide a review of the implementation, and conclude the thesis.

## 1.10 Conclusion

This chapter has described the concepts of scoring and strategies. The credit lifecycle was introduced in the form of an life example, detailing every stage in the lifecycle. A description of the different types of scorecards was provided and their associated use.

The benefits to both the customer and the bank has been described with the ultimate goal is defined as satisfaction from both areas on different measures, sustainable profit for the bank and service satisfaction for the customer.

Chapter 2 describes the research methodology of this research project in detail.

# CHAPTER 2: Research methodology

## 2.1 Introduction

Chapter 2 introduces the research methodology followed in the study. Section 2.2 gives a general overview of the research methodology and depicts the steps followed to model a approach to strategy champion-challenger design, implementation, re-evaluation and re-deployment.

## 2.2 Proposed model of a champion-challenger approach

Implementing a champion–challenger in a retail-banking environment involves interaction on various levels. In order to identify these levels, the proposed methodology of implementation must be considered.

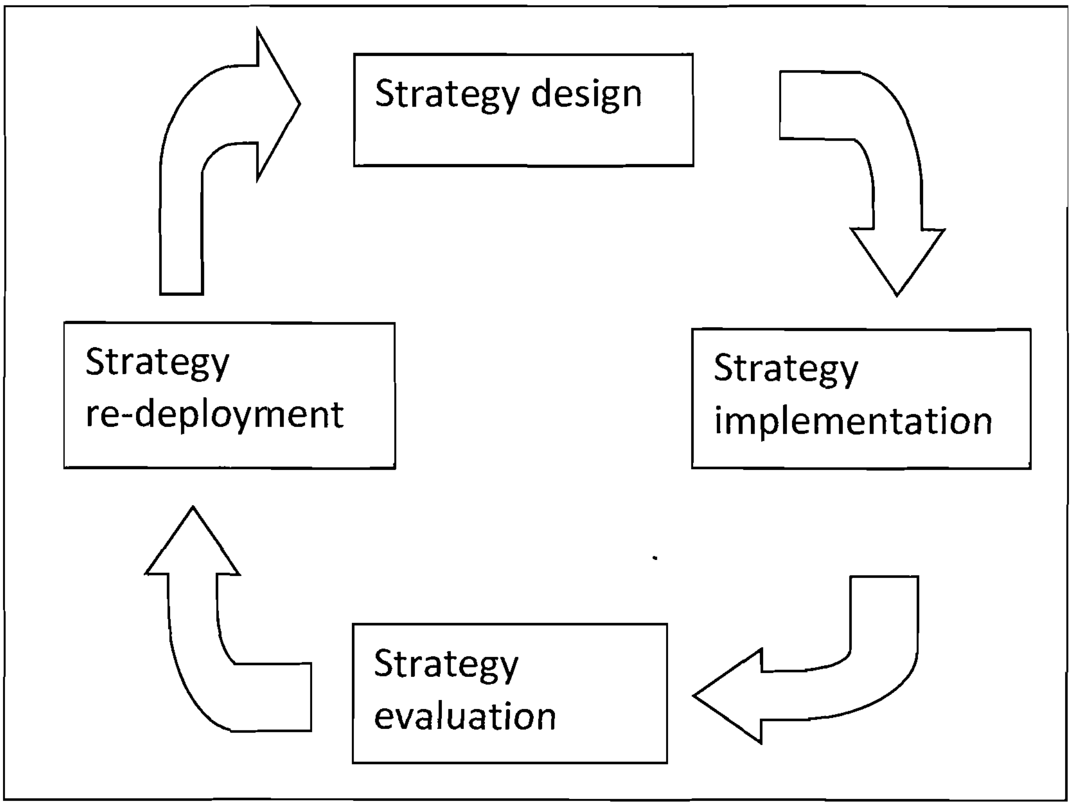


Figure 4: Implementation methodology

Figure 4 represents the process of designing a champion–challenger strategy. Each one of these phases will affect different departments and people in the organisation, in order to deliver to the customer and ensure that the implementation and test is performed. The four phases of the design are discussed in the following section in detail.

### 2.2.1 Strategy design phase

The strategy design phase followed in the study, consists firstly of a clearly defined strategy aim, determining the main objective. Thus, if customers are to be retained, maximising retention would be the strategy aim. As with retention, similar strategies could serve as the aim, such as reducing risk, increasing profit, and maximising attrition. The aim of the strategy should also intend to be beneficial to both the customer and the bank. According to Rhode (2003), the simulation of different constraint scenarios enables one to identify potential strategies that best meet business objectives.

After the strategy aim has been identified, the actual strategy segmentation can be done. Considering the example of modelling for less risk, the clients would be modelled according to their risk profiles in the portfolio. The same applies for other strategy aims, such as profitability and retention. A sample population is identified through analysing the total population and sub-sections of the total population for possibilities of optimisation.

Once the opportunity has been identified and agreed upon, further analysis and planning can take place, and a challenger strategy can be formulated from the identified opportunity. Considerations should be given to the type of challenger chosen. A challenger that has the strategy aim of minimising risk could potentially lead to loss in terms of contribution, as clients that are of a higher risk obviously have other profit drivers, for example, debt management systems charging the customer a additional fee if they go in excess of their limits.

A sample should be taken from the sub-population that represents the differentiating qualities of the sub-population base. A representative group of 10% of customers would adequately represent the group. According to Love (2002:2), a sample size of 5% to 25% of the population group will suffice. A selection of the population should, however, be random from the strategy segment, to ensure representation from the diversity in the sub-population. Once a random representative sample has been identified, the next step is to identify the results that will indicate a 'winning' strategy. It is very important to track the correct variables, in order to measure the success or demise of the champion and challenger.

Assessing the operational impact of the proposed strategy must take place when the viability and implementation path of the strategy is determined. Operational impacts include actions, such as telephoning the customer, sending the customer a courtesy letter, and loading the new offer onto the customer's profile.

Optimisation of the strategy can take place once all the other potential pitfalls have been addressed, as the above-mentioned steps could have shed new light on the strategy. According to Belniak (2003:2) optimisation is a mathematical methodology used to make decisions that achieve an overall objective. The optimisation would take place on the offer made to the customer and different scenarios would be revised, for instance, the interest rate for different risk profiles to which the offer is sent. During decision modelling, a graphical model is built for the problem, the mathematical relationships are then established, and a research data set created.

### 2.2.2 Strategy testing

During the strategy optimisation, a recent master file snapshot is used to simulate impact of the baseline strategy, using the decision model. An estimation of the impact of the strategy should be made and compared to the baseline results. The strategy should be designed to test specific business objectives. The business objectives may include keeping the risk profile the same or improving on it, increasing profitability, and improving retention. Strategy optimisation can be improved by simulating the probable outcome of the implementation, to measure the outcome. Adjustments can be made, to ensure the best results. During simulation, the totality of the process is tested and potential problem identified. Thereafter, planning can take place to reduce the risk of problems arising.

### 2.2.3 Timelines

The period in which the challenger will be implemented must be predetermined, in order to gain the maximum benefit. Criteria that could influence the time are, for example, the calculation of risk scores. The window period for screening and implementing the challenger is defined by this time-period as a customer's details may vary daily.

### 2.2.4 Data dictionary

The refinement of the strategy for interpretability would typically include a data dictionary. This is because most databases have acronyms for column names. Many business owners do not know what the variable names are, and for clarity, the use of a data dictionary is encouraged, as the business owners are required to approve the strategy.

### 2.2.5 Robustness

Furthermore, the strategy should be robust, considering the diversity of clients. An example would be that of identifying customers for a challenger and implementing the strategy without giving them the option to decline the offer. Robustness ensures that the customer is serviced and the process does not have to be adjusted. Ease of implementation can be seen where one could have a limit change and 300 customer limits would have to be changed, one could employ a number of people, to capture the new limits, which is cumbersome, or make use of technology, to enter the data automatically.

### 2.2.6 Stakeholders

Refining the strategy until the business rules (willingness of the business to extend credit based on the level of risk) and set objectives are met involves possible meetings with stakeholders and drawing up service level agreements, to ensure that the correct result is obtained as defined. Business rules, for instance, that exclude customers with foreign addresses or give public telephone numbers as personal telephone numbers have to be removed, to ensure a greater benefit and optimise the use of all resources involved. If one takes into consideration in a situation in which a call-centre employee telephones a public telephone number for a customer contact, and has to hold for the person to make it to the phone, or possible fraudulent syndicates operating from public phone systems, to ensure their anonymity.

### 2.2.7 Strategy refinement

As part of the strategy evaluation, the strategies are refined for interpretability, robustness, and ease of implementation; solutions are built in tree format; and the tree is refined until the business rules and set objectives are met (Fair Isaac, 2003). The tree's branches are based segments that have been identified as segments with different levels of risk (bad rate one month forward roll probability). The tree is refined until no such segments can be identified or the volume of account is to low to proceed.

### 2.2.8 Strategy implementation phase

Once the optimisation has been tested and the portion of the population that has been identified as the challenger is handed over to the marketing team, which has set up the material for the customers explaining the new limit allocated, customers are given the opportunity to reply to the offer. There are thus a number of activities that have to take place prior to implementation. First, the objective of the champion–challenger is to be identified and communicated to the marketing team. Second, the way in which the communication will take place must be agreed upon (for example, telephone, post, or SMS). Third, the new limits must be changed on the product host system on the mainframe, thus an interface into the product system must be arranged. The format in which the Infrastructure team needs the data, to make the changes, is to be identified and agreed. Once this has taken place, the data architecture analysts can prepare the data. If something is considered a formal change and not part of maintenance, a formal change request must be submitted to the relevant information technology team. Lastly, when customers agree to the new limits, the information is captured, and the limits loaded according to the agreed methodology. Once all the customers in the identified challenger population have either agreed or disagreed with the load of the new limit, the evaluation of their performance starts. The marketing team can now measure predefined statistics on the take-up rate (number of taken up offers divided by the total number of offers made) and so on.

### 2.2.9 Strategy evaluation phase

Although implementing a challenger makes good business sense, it is a novel idea and thus it must be proven that the initial aims have been met. In a systems development life cycle, this phase would equate to the testing phase, but because it is not a pure information technology application, the term *evaluation* is used.

The components involved in the strategy that have to be tested are:

- business rules and regulations;
- client satisfaction;
- risk exposure;
- profit for the bank; and
- operational process flow.

Business rules and regulations

In order to manage credit, business rules are created to make similar decisions from different applications. Business rules typically include information, such as the cut-off score from a credit bureau. Thus, if a customer scores above a certain score their loan request is accepted, otherwise it is rejected. Other examples include customers with judgements in the last year, who would be declined upfront (this is termed *upfront exclusions*).

Client satisfaction

Customer satisfaction is always difficult to measure, thus all contact points to the customer and the interactions thereof should be monitored and reported. Information, such as the number of times clients have been in excess of their limit, should be taken into account when developing the refined strategy, as penalty fees are charged for each one of these events.

Risk exposure

The excesses on the new assigned limits to the customer should be monitored, as this will drive the good/bad definition on the account.

Profit for the bank

Since there is a greater scope for utilisation, a greater amount in interest charges should be generated from these customers.

Operational process flow

The implementation of the champion–challenger should be auditable and clear records should be kept of the process followed, to implement the new limits. Any incidents should be recorded, for the improvement of the process in any further attempts. In order to prove that the champion–challenger was indeed successful, one should consider all the above-mentioned components and design tests to measure each, which is described in detail later in the study. Before the actual implementation of the test, it would be advantageous to simulate the probable outcome. Before attempting the challenger strategy, a suitable period of application should be agreed upon by all the parties involved. Because some of the components make use of a human component, performance measurements should be in place to measure if there was a significant operational impact or not.

The results from all the evaluations, marketing, and credit risk, are complied, and conclusions derived from the reports, which would recommend either the champion or the challenger as the operating strategy.

### 2.2.10 Strategy re-deployment phase

The strategy deployment phase is entirely dependent on the measurements in the strategy evaluation phase. It would be foolish to implement an unsuccessful challenger to the base, thus there would be some adjustments and re-testing in the evaluation process until the strategy proves to be beneficial.

It is possible to run more than one strategy at a time. If more than one strategy were evaluated, the winning strategy would be selected and implemented to the champion (the rest of the base that was not part of the selected challenger). From the evaluation, one would see the impact that the strategy has had on the total system (operational impact included), and then establish the strengths and weaknesses. All actions and results should be recorded, to serve as reference for subsequent tests.

## 2.3 Conclusion

Chapter 2 has given a description of the research methodology. The methodology was broken into its different phases namely strategy design, strategy implementation, strategy evaluation and finally the re-deployment of the strategy that has been identified as the best.

Environmental measures were introduced, for example where the timelines of the intended testing has to be defined and a data dictionary must be compiled, to ensure overall understanding of the data.

Chapter 3 describes the process of identifying an opportunity to optimise a strategy that is not performing as intended, or with a slight adjustment can yield far better results.

# CHAPTER 3: Analysis in selecting a champion–challenger

## 3.1 Introduction

The selection of a population to optimise is the most important step, as the selection will determine the success of the champion–challenger. The total portfolio has to be analysed, to seek opportunities where optimisation would be beneficial. The analysis of a portfolio typically includes monitoring the underlying scorecard (determining accuracy, checking whether performance is still as intended) and the strategies associated to the scores (ensuring the various segments in the strategy are treated as intended). Love (2002) states that champion–challenger testing capabilities allow financial institutions to continually validate and improve their models and strategies.

In order to identify an opportunity to test champion and challenger strategies, a scored portfolio has to be identified. If all the portfolios were being monitored at the same time a choice would have to be from the portfolios that are being monitored. If a suitable monitored portfolio is identified, the monitoring report for that portfolio is scrutinised to identify possible opportunities to improve existing strategies.

The bank in this research project makes use of a parameterised decision delivery system. The credit department performs changes and implementation. According to McNab and Wynn (2003:86), one of the leading systems available in the market offers the following components:

- strategy definition, which facilitates the design of strategies;
- strategy execution, which applies strategies systematically;
- data manager, which manages access to internal/external data;
- reporting, which monitors strategies;
- scoring, which is the decision engine for producing scores and associated decisions; and
- bureau connection, which manages calls for bureau information.

If one considers credit risk, a transactional account is more indicative of risk than a loan product, because a customer would first pay the mortgage or asset-based finance product, because they need a place in which to live and a car to get to work and back. For this same reason, customers would use their transactional products to cover any shortfall in their loan products.

Monitoring capabilities and data are available for all the portfolios that the bank offers. It was decided to run the champion–challenger on a transactional product, specifically current accounts with overdraft facilities, since the product is more indicative of risk, and would show earlier signs of success or failure.

In this chapter, scorecard monitoring is discussed in detail in Section 3.2. Thereafter, the analysis findings are presented in Section 3.3. In Section 3.4, the sample group and population are defined and discussed. Lastly, in Section 3.5, operational impact is detailed.

## 3.2 Monitoring

### 3.2.1 Monitoring a scorecard

To monitor a scorecard it would be beneficial to understand how the scorecards are developed and what is the intended purpose there of.

Scorecard development

The philosophy behind scoring according to Mays (1998) is to use past information, to predict the future performance of applicants, or behavioural performance. It is assumed that a relationship between characteristics at the point of application or observed behaviour is different for good and bad customers. Based on the above-mentioned assumptions, the separation between these groups can be predicted. According to van Heerden (2002:1) even the best models have to be monitored continually to ensure optimal performance of a portfolio.

The credit scoring process is a process whereby a calculated numerical weight is assigned to each predictive variable (characteristic) on a credit application or behaviour at a point. The score for each characteristic is determined by the classed value (attribute) the characteristic has for the application or behaviour at a certain point. The individual weights are then totalled, with the total score representing the risk of the application of the estimated risk for a behaviourally-scored account (Mays, 1998).

Siddiqi (2006:17), McNab and Wynn (2003:51), and Anderson (2007:220) describe the process of developing a scorecard in varying amounts of detail, but all have process that are common. The following lists show these steps:

Scorecard development steps according to Anderson (2007:220):

1) data preparation;
2) transformation;
3) characteristic selection;
4) segmentation;
5) reject inference (application scoring);
6) scorecard calibration;
7) validation;
8) implementation;
9) overrides, referrals, and controls; and
10) monitoring.

Scorecard development steps according to McNab and Wynn (2003:51):

- feasibility study;
- sample definition;
- data assembly;
- analysis of characteristics;
- reject inference (application scoring);
- scorecard build;
- validation;
- strategy selection and documentation; and
- implementation.

Scorecard development steps according to Mays (1998:170):

- define business objectives;
- gather the best data;
- perform analysis and develop model; and

- implement solution.

Scorecard development steps according to Siddiqi (2006:17):

- preliminaries and planning;
- data review and project;
- development database creation;
- model development;
- scorecard management reports;
- scorecard implementation;
- strategy development;
- post implementation; and
- remedial actions.

From these steps, it can be seen that the scorecard development consists of the steps that follow.

- start-up meeting;
- data collection and overall population analysis;
- good/bad definition;
- sample selection;
- single factor analysis;
- multi factor analysis;
- training;
- calibration and scaling;
- implementation;
- monitoring.

The section that follows provides detail of each one of the steps listed above.

Start-up meeting: In consultation with the business, determine the reason for the development (with reference to current monitoring results, if appropriate), the project scope, major players (especially the scorecard development team), data sources, observation/outcome windows (time-periods), and possible population segmentation.

Data collection and overall population analysis: The data specification is drawn up from the start-up meeting and a request for data is submitted, or the data is collected by the developer. The overall population data is manipulated to suit the modelling methodology, usually the monthly snap-shot data is stacked or aggregated. The performance definition is derived from the data or a standard definition, for example, the ninety (or more) days in arrears for Basel II compliance is coded. Statistics are calculated on the overall population to see if any significant shifts have taken place, which can hopefully be explained by the chronological event log (including marketing and collection effort events). The overall population bad rate is calculated, if the sample bad rate differs from the total population, weights can be assigned to the good and bad accounts, to reflect the overall population.

Good/bad definition: The good/bad definition determines what the model will be predicting. Typically, bad accounts are rare events, and lenders may struggle to get sufficient numbers to build a reasonable model. Ideally, there should be a minimum of 1500 good and 1500 bad accounts, but it is possible to develop a model using as few as 400 of each. The definition may be derived purely from management consensus, but companies today are more likely to base them upon an empirical historical analysis, or use a prescribed accounting or regulatory definition (such as Basel II).

The bad definition may be:

- worst status (ever-down) over a period, such as the Basel II default definition; or
- current status at the end of a period, which is commonly used for provisions modelling. It is crucial to exclude accounts that are obviously bad or extremely high risk at observation, as their inclusion will make the model less relevant for those where the status is less clear.

Sample selection: A representative sample is selected. For almost all credit scoring, defaults are rare events and stratified random sampling is required to ensure there are sufficient bad accounts (this is also referred to as *over-sampling of bad accounts*). The weights for the under-sampled records are increased, to keep the sample and population bad rates in line. The overall population bad rate is calculated, which is used to ensure that the sample is still representative.

The sampling methodology was reliant on the regression or non-linear estimation technique that was used to calculate the score, there are assumptions of normality in, for example, the iterative search methodology or the assumption of independence between observations for logistic regression. Thomas (2000) states that the classification results produced by linear and logistic regression are very similar and both are sensitive to correlations between predictive characteristics.

Single factor analysis: Most credit scoring models are developed using relatively large samples (for example, greater than 1000 bad accounts). This allows the luxury of using classed characteristics, which are extremely well suited to handling non-linear relationships with the target (for continuous characteristics, the alternative is to either use the variable directly, or use some simple transformation, for example taking the natural logarithm of all the values). The first task is to determine the optimal groupings for both numeric and categorical characteristics. The goal is to have the smallest number of groups (attributes) for each characteristic, but with minimal loss of power. This involves pooling groups with similar bad rates (which for continuous and ordinal characteristics must be adjacent classes). After the process is completed, each of the attributes must have sufficient cases, to ensure that the weights assigned by the model are robust.

It helps to view the attributes' weights of evidence graphically (in conjunction with the calculated overall strength), to see whether the relative strengths make sense. It is also important to ensure that the number of good accounts (and/or bad accounts) per attribute are sufficient. At the same time, it also helps to compare the resulting distributions against a more recent sample, to ensure that it will still be valid when the model is implemented.

Once the strength of the characteristics has been measured, the characteristics that are obviously not predictive can be dropped, such as those with much missing information and weak strength.

Multi factor analysis: At this point, the correlation between characteristics is measured. If the correlation between any two characteristics is high (in excess of 60%), the preference is for the strongest one, assuming that it also makes logical business sense. An extreme example of this is characteristics that suffer from autocorrelation, such as days past due last three months and days past due last six months. Alternatively (or in addition), reliance can be put on the statistical modelling technique to include or exclude the appropriate characteristics, albeit with some human oversight. Regression techniques allow forward, backward, and stepwise selection, to establish which characteristics contribute most to the overall model. Those that do not feature can be removed from the candidate list upfront.

Training: There are different methodologies that can be used to model binary outcomes (such as default or not default), and finally scaled to a score. Some of these are:

- Linear discriminant function;
- Logistic regression;
- Neural networks;
- Mathematical/goal programming;
- Predictive decision trees.

A brief description of the development methodology is given below, with the methodologies associated advantages and disadvantages.

- Linear discriminant function (LDF; Mays, 2005:216):
  - advantages
    - computationally easy and efficient.
  - disadvantages
    - less power than logistic regression;
    - no direct relationship between the score and the percentage of the event; and
    - the approach is optimal when requirements for population distributions are met (normality and equal variances across the groups).
- Logistic regression (Mays, 2005:216):
  - advantages
    - no assumptions on the distribution of the population, such as normality and equal variances and covariance.
  - disadvantages
    - requires more computational power than LDF.
- Neural networks (Mays, 2005:216):
  - back-propagation network
    - typically contains an input, hidden, and output layer.

- advantages
    - hidden structures between input characteristics can be captured; and
    - often the performance is superior to conventional approaches when the optimal structure is used.
- disadvantages
    - parameter estimation is not intuitive (black box) and is hard to control; and
    - computationally, it is expensive and takes a long time to learn.

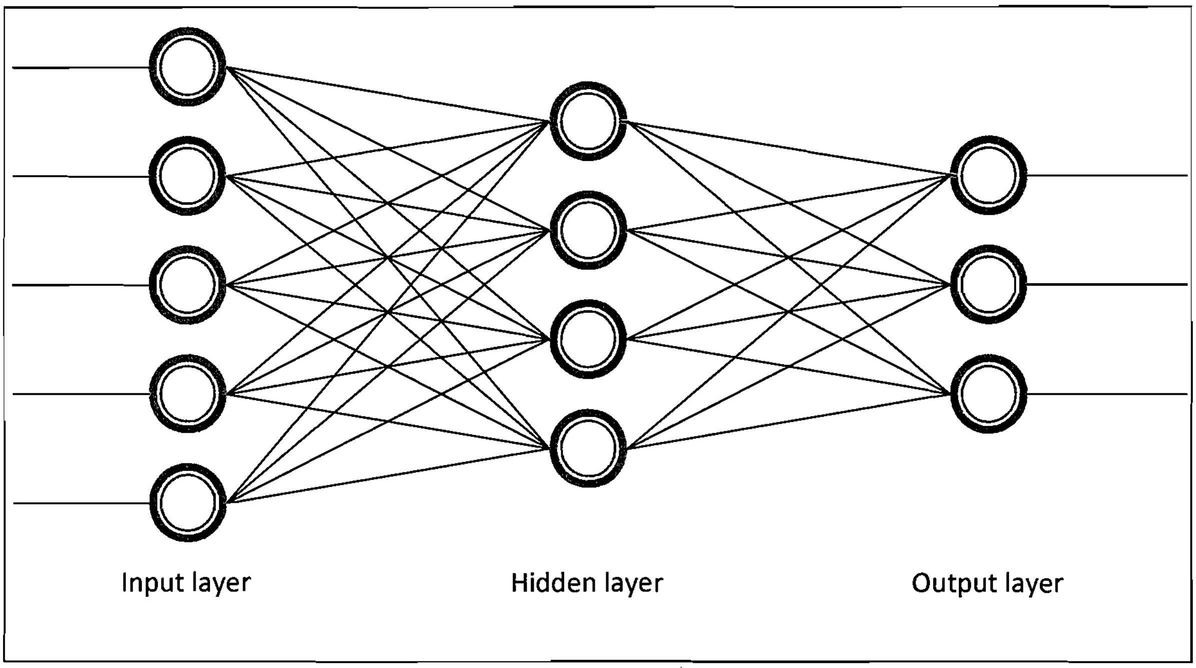


Figure 5: Neural network representation

- Mathematical/goal programming (Coello Coello, 2008:42):
    - advantages
        - the methodology is not complex to use and simple to implement.
    - disadvantages
        - In some cases defining the goals is difficult, and this could lead to extra effort during computation resulting in extra costs; and
        - in producing the solution in the Pareto optimal set, goals must lie in the feasible region.

- Predictive decision trees (Thomas, 2004:15):
    - advantages
        - unexpected relationships can be highlighted through the model development;
        - the differences in subgroups are highlighted through simple statistics;
        - could build a model with either categorical or continuous variables; and
        - missing data can be handled.
    - disadvantages
        - false relationships could be identified; and
        - results are difficult to present.

Once the final model is developed, the weights for each attribute (only those that feature in the model) are reviewed, to ensure they are consistent in terms of size and direction of their bad rates. The overall model strength also determined, both for the training and hold-out samples.

Calibration and scaling: The score produced from a linear regression has an arbitrary score value. Many institutions have a common score grade between products. Thus, a score of 600 for a vehicle and asset-based finance product is equivalent to a score of 600 for a current account. The process of getting the scores to indicate the same risk is termed *scaling*. In order to compare the products, the bad definitions should be the same or at least indicate the same level of risk. Thus, the good/bad odds are calibrated as well.

Dependent on the decision engine capability and the strategy followed by the lender, the score is calibrated and scaled, for example, a score of 660 with the odds of 15:1, and the score doubling every ten points.

Implementation: Dependent on the decision engine capability and the strategy followed by the lender, the score is calibrated and scaled, for example, a score of 660 with the odds of 15:1, and the score doubling every 10 points.

Strategies are set for the score and coded into the decision engine along with the scorecard, where a scored sample from the development is used to verify that the scorecard has been implemented correctly. The strategies are tested at this stage in the test environment, to ensure that the strategy works as intended.

Monitoring: the frequency and types of measures are defined for the scorecard and will depend heavily on the type of scorecard implemented, for example, the application or behavioural scorecard.

Scorecard monitoring

Mays (1998:285) suggests that the monitoring or tracking effort should start as soon as has been implemented and information is available to perform the analysis.

Measurements used quarterly to monitor a scorecard typically include:

- Score distribution comparison (actual versus expected) report: This report is used to see if the actual score distributions have changed from that of the forecasted (expected) distributions. If the shift has a K-S test maximum observed difference of over 10% and this difference is significant at the 5% level, then there is a need to investigate further, probably by conducting characteristic point shift analysis.
- Score distribution comparison (actual versus historical) report: This report compares the score distributions generated in the current month with the previous month and with two additional time periods. This report augments the actual versus expected score distribution report, by showing whether there has been a meaningful score shift from expectations. For example, if the actual versus expected score reports shows a K-S over 10%, and it is statistically significant at the 95% level, this report can help to determine if the score shift is a trend, a constant shift, or has just occurred this month.
- Score performance (good versus bad) report: The Gini co-efficient (a summary statistics of the Lorenz curve) is a measure of the strength or efficiency of the scorecard. It measures how effectively the scorecard separates the good from the bad accounts. This report verifies that the model is still ranking risk on a population of accounts. The [odds and Ln (odds)] report: The score performance [odds and Ln (odds)] report uses good/bad odds and Ln (odds) to monitor the risk-score relationship. This report compares the odds and Ln (odds) of good accounts and bad accounts. It displays the performance of accounts over a fixed period, that is twelve months. The scorecard's validity can be assessed by observing the Ln(odds) versus score relationship. If the slope of the ln(odds) graph is positive, the scorecard is still ranking risk (Mays, 1998:297)

Front-end and back-end reports according to Anderson (2007:473) include the following:

<u>Front-end reports:</u>

- score drift: characteristic and score level drift of the population and operations;
- selection process: the applicant volumes and the final number of taken up accounts (application scoring); and
- override reasons: monitoring where a system's decisions have been overridden.

<u>Back-end reports:</u>

- portfolio analysis
  - delinquency distribution: shows the spread of accounts according to some measure that has traditionally been considered highly indicative of risk, such as days past due; and
  - transition matrix: shows the movement between different buckets over a specified time period, where the buckets are defined by delinquency, value. and other attributes.
- performance tracking
  - scorecard performance: analyses the distribution of delinquencies by score;
  - vintage analysis: analyses changes in the portfolio performance over time; and
  - score misalignment: a tool to measure discrepancies, at characteristic level.
- drift reporting
  - population stability reports: a report that tracks the change in characteristic distributions over time (commonly used on a classed score), comparing actual versus expected; and
  - score shift reports: identifies the shift in score distribution, at score or attribute level.

The cycle on which a scorecard is monitored will depend on the resources available to perform the monitoring exercise. It is common practice to monitor a behavioural scorecard on a quarterly basis. The scorecard in this study is monitored on a quarterly basis.

Developing a strategy

As with monitoring a scorecard, understanding the development of a strategy enhances the understanding of monitoring a strategy. As mentioned in the previous section, the strategies are defined after the behavioural score has been developed. McNab and Wynn (2003:107) state that it is important to understand that when setting strategies the following holds true:

- The score itself does not set the strategy, it is a predictor of risk.
- The success or failure of a set strategy cannot be predicted accurately, as the aim of the strategy is to influence customer behaviour.
- Good strategies are developed on empirical evidence.
- Controlled experimentation needs to be carried out, to understand the influence of the strategy on the customer's behaviour (champion–challenger).

For transactional products, limit-setting strategies are typically set at the end of the scorecard development process. These confidential, or shadow, limits are the maximum amounts that the bank is prepared to extend to each customer, over and above the declared limit (assuming it is lower). They are recalculated every month, using the same score and strategy algorithm, to reflect any changes in customers' income or behaviour. These limits are not communicated to the customer, but are instead used as a benchmark for adjusting the declared limits, whether as part of a campaign, or upon customer request, or in response to deteriorating behaviour. Limit strategies thus reward good behaviour and penalise bad behaviour, by managing the declared limit up and down, respectively. Limit increase campaigns will typically be run monthly, for all accounts that have not had a limit increase in the past year, and have not already been campaigned. In contrast, limit decreases will only be affected when a customer's behaviour is deteriorating.

Monitoring a strategy

Since the strategy and the score are so closely related, it makes sense to monitor both at the same time. For application scoring, cut-off strategies can be monitored after the first month's applications have been recorded, and some time has elapsed to evaluate their performance. The same applies to behavioural scoring; an elapsed three to six months data is sufficient to provide early indications, while twelve months will prove whether the intended results are being achieved.

A good strategy experiment has clear measurable objectives, is run over a limited period, consists of a limited sample of the overall population, and has thorough operational planning (McNab & Wynn, 2003:118).

Monitoring of the experiment should focus on the elements of the champion strategy that are being questioned, such as the average good and bad balances. McNab and Wynn (2003:119) also mention:

- new limit take-up rate;
- balance;
- interest income;
- fee income;
- delinquency;
- write-offs; and
- operational cost.

Bringing these elements together can provide an indicator of likely change in profitability. This also requires information on interest funding costs (to calculate net interest revenue) and provisioning policy (to calculate expected write-offs). The calculation used to generate the reports below is:

Contribution = Net interest + fees income – provisions – write-off – operational costs.

Given that the goal was to test the reward of good behaviour of customers, and see whether they take advantage of the increased limits, a group with medium to low risk attributes was chosen.

In the following section, the analysis findings are presented.

## 3.3 Findings

In order to identify a suitable population upon which to be experimented, a full set of reports were compiled as part of scorecard monitoring. Figure 6 shows how limit management reports, which depict key balance and limit figures, can be presented graphically. Such reports would be produced for different risk bands in market segments of interest. Reviewing these reports could prove to be a daunting task if the number is large, for example, even for the relatively straightforward case of two market segments with nine risk bands each, eighteen graphs would have to be produced and interpreted.

A limit management report would typically include:

- number of accounts in the market segment;
- average credit turnover;
- average confidential/shadow limit;
- average current assigned/communicated limit; and
- average minimum balance.

These averages and values are calculated each month and graphed over a period, usually twenty-four months (where available).

From the monitoring exercise performed on the medium risk group (general market segment), a champion–challenger, an opportunity was identified:

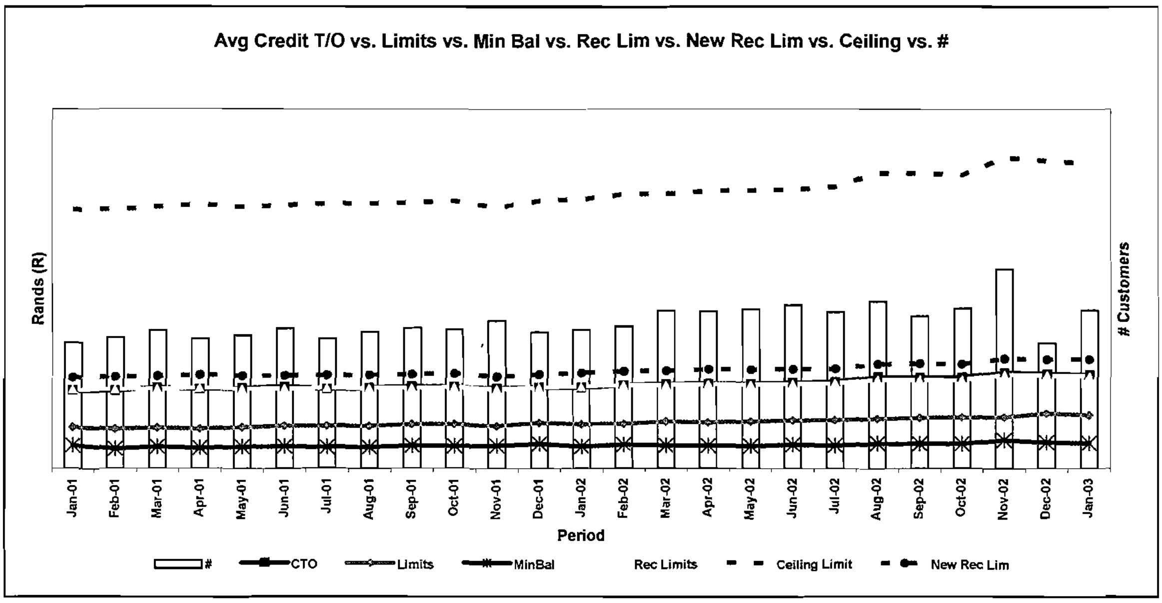


Figure 6: Finding a champion–challenger

In Figure 6 the legend:

- # – represents the number of accounts
- CTO – represents the average credit turnover of the accounts in the category for the month
- Limits – represents the average limit allocated to all accounts in the category for the month
- MinBal – represents the average minimum balance of the accounts in the category for the month

- Rec Limits – represents the average recommended limit of the accounts in the category for the month
- Ceiling Limit – represents the average ceiling limit of the accounts in the category for the month
- New Rec Lim – represents the newly calculated average recommended limit of the accounts in the category for the month

The particular market segment and risk grade population depicted in Figure 6, shows an opportunity to adjust the population's communicated limit (*Limits*) proportionally to the ceiling/shadow limit. The recommended shift is depicted as the recommended limit/new recommended limit based on different adjustment factors.

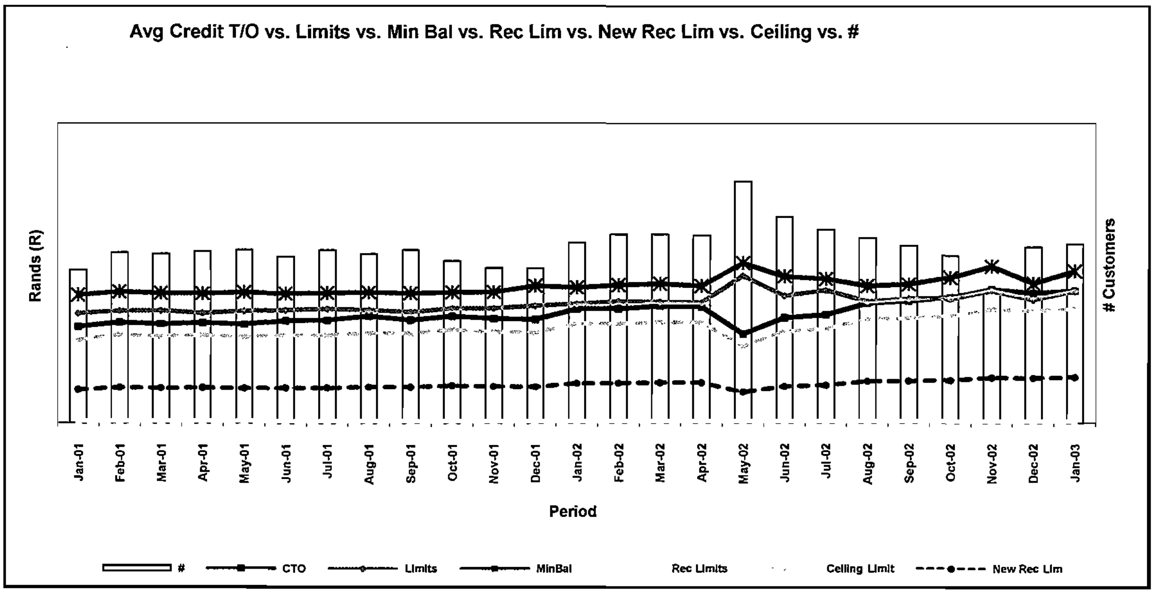


Figure 7: Example of a population that is not ideal for a limit strategy change

Figure 7 depicts a segment of the overall population where it would not be advantageous to implement a limit increase strategy, because the average minimum balance for the segment is already over the limit.

The sample group and population are discussed in the next section.

## 3.4 Sample group and population

Once a segment of the population has been identified as an opportunity to experiment with the limits, the experimental design is defined. As discussed in Section 2.2.1 a small but representative sample is taken from the identified segment, to limit the impact of the experiment if it is unsuccessful. Figure 8 shows the process flow for selecting the random set of customers to serve as the challenger population. This sample is then used by the campaign management team to create the workflow. The sample and the rest of the segment are defined, and the two sets of data are used as the base for the monitoring exercise to follow.

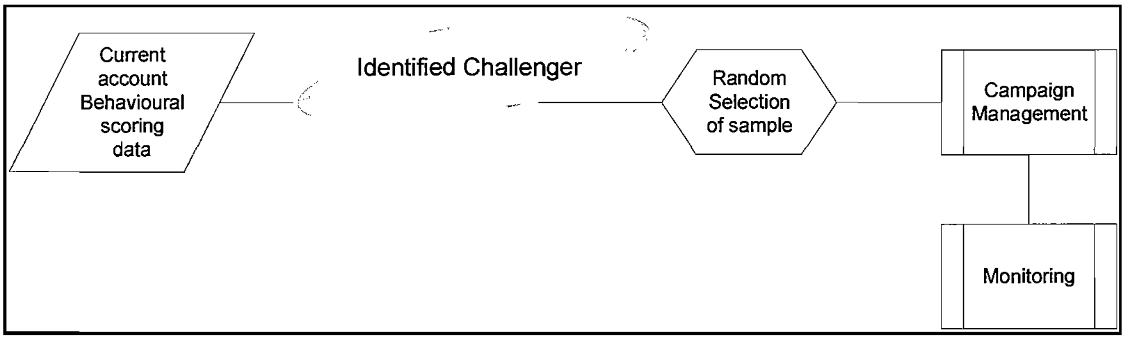


Figure 8: Champion–challenger sample creation

Finally, the operational impact of the exercise is detailed.

## 3.5 Operational impact

Because the purpose of a strategy is to influence the behaviour of a customer, a change to that strategy introduces new influence on the customer. It is thus of critical importance to manage the experiment diligently.

The number of accounts used to perform the experiment should be relatively low, to limit the negative impact should the experiment go awry. Operationally, the strategy will affect the following operational environments:

- the current account system;
- the campaign management team;
- the credit analytics team;

- the bank's call centre;
- the data management team;
- the credit systems innovation team; and
- the credit management team.

It would be advantageous to project manage the experiment, by assembling a project team with representation from the relevant areas listed above. The following step-by-step guide can be used to guide stages in the project plan for the champion–challenger experiment:

- kick-off meeting;
- sample design;
- strategy optimisation (analysis and feedback);
- implementation planning (campaign specification, credit systems change management, and monitoring definition);
- implementation;
- measurement; and
- feedback and recommendations.

The above steps were followed as part of this exercise.

## 3.6 Conclusion

The chapter has described the model development process and the monitoring process, and provided an example of how to identify a possible opportunity of creating a champion–challenger exercise.

The methodology used to develop a scorecard is the choice of the organisation, as has been discussed there are advantages and disadvantages to the various methodologies. The population will drive the choice of the methodology. The advantage of developing scorecards internally certainly has advantages, if enough work is available to employ analysts.

This chapter has also emphasised the critical importance of monitoring a scorecard. The monitoring information informs the users that the scorecard is either performing as intended, or needs some work to be done. If the environment for monitoring scorecards has been automated, the report generation can then be undertaken more frequently, and problems can be identified and resolved much faster.

Chapter 4 will discuss the simulation and testing used when considering a champion-challenger strategy testing. Measures are defined to measure the success or failure of the champion and challenger. These measures are broken up into immediate, interim and final evaluation measures. Some reports are defined to assist obtaining buy-in from stakeholders.

# CHAPTER 4: Simulation/testing

## 4.1 Introduction

In order to prove that a change in strategy has impacted any of the customers negatively or positively, it is wise to first test the proposed change on a smaller but representative portion of the population. The very nature of a champion–challenger strategy change mechanism is that it is a test or simulation of the influence the proposed strategy will have on the greater population. The results from the tests show which of the two, champion or challenger, is the true victor.

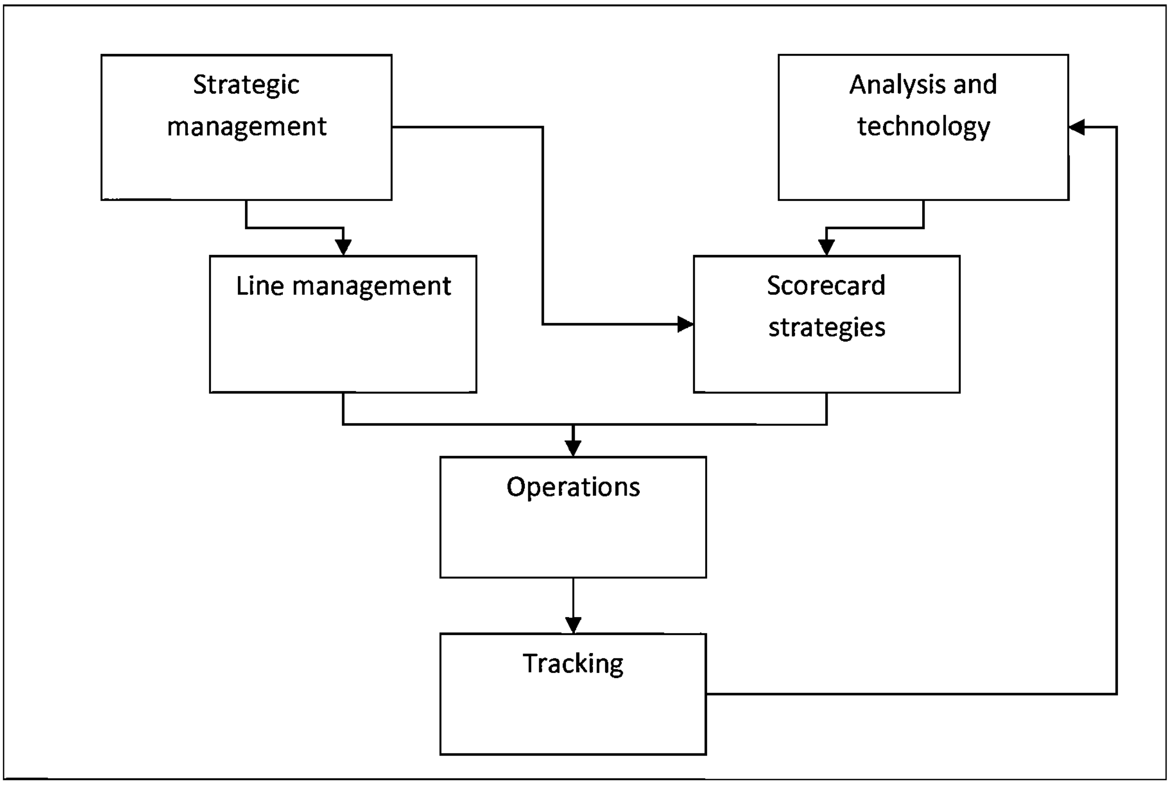


Figure 9: Feedback loop — today's control structure

Scallan (2007) describes a feedback loop depicting today's structure of control as can be seen in Figure 9 above. He mentions that today's feedback loop enforces centralised control. A technology and analysis are employed, the strategy changes can only be made after feedback has been provided after a full cycle, which results in strategies evolving slowly.

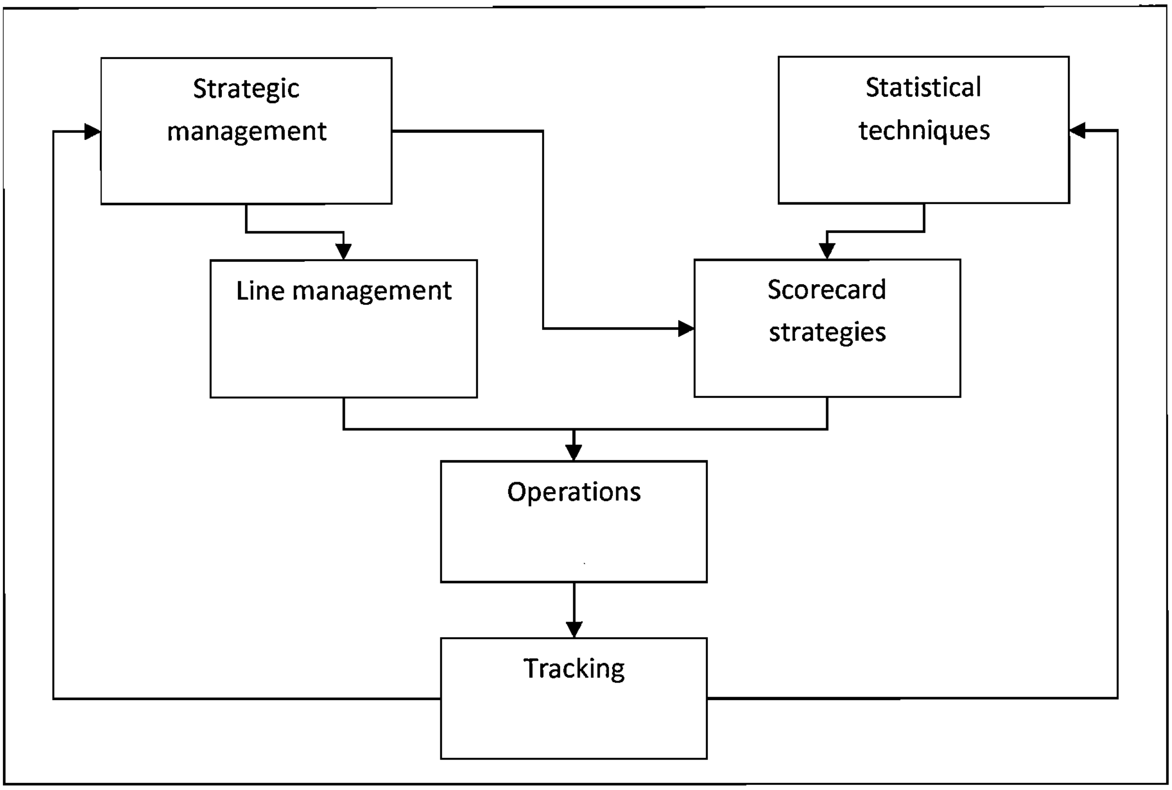


Figure 10: Feedback loop — future (Scallan, 2007)

Figure 10 depicts the future of the feedback loop, where strategic management is informed about the tracking of the scorecard strategies. Another change from the current feedback loop is that statistical techniques (neural networks), rather than analysis and technology are used to modify and optimise the strategies.

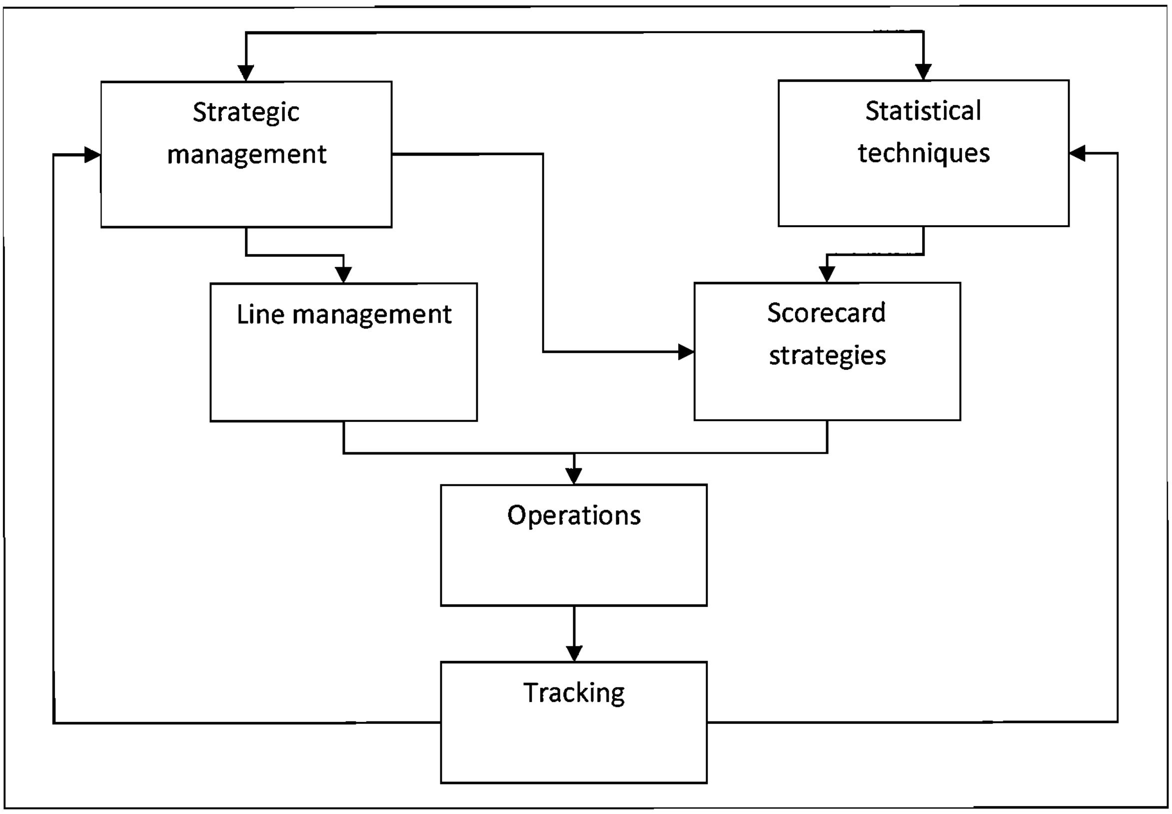


**Figure 11: Leveraging the feedback loop (Scallan, 2007)**

Strategic management is responsible for setting strategies that obtain the greatest benefit from the available scorecards. As such, it needs to have a good understanding of how scorecards influence the process and the intricacies of tracking strategies. Only then can confident decisions be made regarding further enhancing the strategies, and hence the business.

From the above discussion, it can be seen that the key is to have tracking and statistical practices in place. The following section describes a report used to compare the champion and challenger strategies that was presented to the strategic management team. Interaction between them and the analysis team will ensure that the strategy is optimally designed and implemented.

In this chapter, the measurement milestones are defined in Section 4.2. Thereafter, the strategy monitoring reports are presented in Section 4.3. Next, the strategy test methodology is explained in Section 4.4. Following this, the data market for monitoring is presented in Section 4.5. Lastly, measures of success and failure are defined in Section 4.6.

## 4.2 Defining measurement milestones

### 4.2.1 Immediate feedback measures

After the experimental strategy has been implemented, the first opportunity to measure the outcome, confirms whether the strategy is influencing customer behaviour as intended.

Immediate measures for a champion–challenger include monitoring on the operational area (client impact), account behaviour on the champion population, and account behaviour on the challenger population. The measurements based on these areas serve as early warning reports for the various areas impacted. In terms of measuring the operational area, the impact made on the customers needs to be considered. Common measures are the number of calls made by the contact centre, the take-up rate, and complaints received. Early warnings on account behavior monitoring are commonly measures that indicate how customers are utilising the new limits.

### 4.2.2 Interim feedback measures

Once a strategy has provided sufficient evidence of no adverse initial impact, it is left in the operational area. After a predetermined period, the strategies are re-evaluated, to investigate whether or not the strategies are still performing as intended. In the case of the limit increase strategy champion–challenger, the intended purpose is to increase limits of acceptable risk customers with a need for greater limits, in such a way that the customer's risk is not adversely affected and that the limit assigned is utilised. Measurements used to monitor this purpose include the customer's risk profile from the point of change, the utilisation of the limit following change, and the interest in fee income produced by the utilisation of the limit.

### 4.2.3 Final evaluation

The final-evaluation report will consolidate the full life cycle of the experiment. It will thus include the initial measurement reports, the interim measurement reports, any further analysis, and recommendations.

Further analysis will provide additional information on the measured period after the experimental period's measurements of the customer's credit behaviour. Once the final report has been produced, it is evaluated by strategic management, and the best strategy is implemented. The total end-to-end process is documented and retained for future reference.

The strategy monitoring reports are presented in the next section.

## 4.3 Presenting the strategy monitoring reports

The success or failure of the challenger is determined by strategic management, based upon the information with which they are provided. As described above, there are three different milestones, each with a different set of measures. In order to calculate these measures, the following details have to be recorded for each account, as shown in Table 1.

Table 1: Strategy-monitoring report characteristics

| | Characteristic | Report | Measurement purpose |
|---|---|---|---|
| 1. | Average credit balance | Interim/final | Credit risk |
| 2. | Average debit balance | Interim/final | Credit risk |
| 3. | Average debit interest | Interim/final | Credit risk |
| 4. | Average fee income | Interim/final | Credit risk |
| 5. | Collection statuses | Interim/final | Credit risk |
| 6. | Good/bad rates | Interim/final | Credit risk |
| 7. | Take-up rates | Initial/final | Marketing |
| 8. | Call-centre complaints | Initial/final | Customer management |

### 4.3.1 Initial monitoring reports

As mentioned in the previous section, the initial contact results and credit behaviour have to be assessed. Measures used to analyse call-centre contacts typically include the number of customers that have been contacted successfully, the response from the customer (accepted or rejected) and the cost associated to call centre activities. Table 2 gives the call-centre activities and details the operational measures required. Table 3 depicts the values and volumes of the campaign, and Table 4 presents the cost incurred, namely the cost associated with the number of actual contacts made with targeted customers.

Table 2: Outbound call statistics (initial contact details)

| Records sent | Call attempts | Contacts | Total Sales | Sales to contacts |
|---|---|---|---|---|
| The number of customer records sent to the call centre | Number of calls made by the call centre, to contact the customers | Actual number of customers contacted | Number of customers accepting the offer | Percentage of sales made to customers contacted |

Table 3: Resulting values and volumes

| Data set | Number increased | Value of increases | Average limit increase per client |
|---|---|---|---|
| Number of records sent to the call centre with intended campaign strategy | The actual number of limits increased (accepted by customer) | The Rand value of the limits increased | The average limit increase per customer |

Table 4: Campaign cost analysis

| Total number contacted | Cost per contact | Total cost |
|---|---|---|
| Number of telephone calls made | Cost per call | Overall cost |

Reports required to analyse the customers' credit risk will typically include Account status reports(good Bad) Table 5 depicts the measures to be tracked to assess the credit risk of the customer.

Table 5: Customer credit risk behaviour

| G/B/I status | Cumulative percentage: Bad champion–challenger | Cumulative percentage: Good champion–challenger | Cumulative percentage : Indeterminate champion–challenger |
|---|---|---|---|
| Good, bad, and indeterminate (G/B/I) account status | Cumulative percentage of bad customers | Cumulative percentage of good customers | Cumulative percentage of indeterminate customers |

A crucial indicator is the number of customers in the challenger population that enter the collections area. The report provides a frequency distribution for each of the possible collections statuses.

### 4.3.2 Interim monitoring reports

The interim reports reflect changes in customer behaviour over time. Measures of success relate to whether the customer utilises the higher limit, the revenue generated, and risk profiles. It is therefore important to measure the customer's credit risk (good/bad statuses and collection statuses), the utilisation of the limit (debit and credit balances), and the interest earned from the account. The report in Table 6 was also used to measure the customers' credit risk.

Table 6: Interim customer credit risk behaviour

| Period | G/B/I status | Cumulative percentage: Bad | Cumulative percentage: Good | Cumulative percentage: Indeterminate |
|---|---|---|---|---|
| Measured per month | Good, bad, and indeterminate account status | Cumulative percentage of bad customers | Cumulative percentage of good customers | Cumulative percentage of indeterminate customers |

Table 7: Fee income (interest and service)

| Period | Characteristic | Champion average | Challenger average | Total |
|---|---|---|---|---|
| Measured per month | Debit interest income | | | |
| | Service/penalty fee income | | | |

Table 7 shows the information required to track fee income from the accounts. The expectation is that the average interest income will increase (greater limits) and that penalty fee income (over-limit fees) will decrease.

### 4.3.3 Final monitoring reports

The final monitoring reports consolidate the information from the initial and interim reports, and provide a comparison of results between the challenger and champion groups. A recommendation is made based upon the results as to whether the challenger strategy should be operationalised.

In the next section, the test methodology is explained.

## 4.4 Explaining the simulation methodology

### 4.4.1 Defining the strategy delivery channel

In order to test the challenger, the bank designs a campaign using a specific medium. Customers are notified that an increased overdraft limit is available, and given an opportunity to accept or decline. Limit increase strategies are governed by legislation, such as the National Credit Act (2006). The act stipulates the interaction between the bank and the customer. In 2006, a new act was drafted, which includes extra limitations on marketing credit facilities to customers. The risk of lending and the customer's capacity for debt has to be taken into consideration, and the customer should have the option of accepting or declining the offer.

For each customer contact, there is a predetermined flow of events that must take place before the customers' limit can be increased. As this is an interaction with the customer, it should be a pleasant experience with no unnecessary delays, and if possible, it should be used as an opportunity to cross-sell other products. There are also certain rules/regulations governing the process, for example, customers that have opted out of future marketing campaigns, or who are above or below certain ages must be excluded.

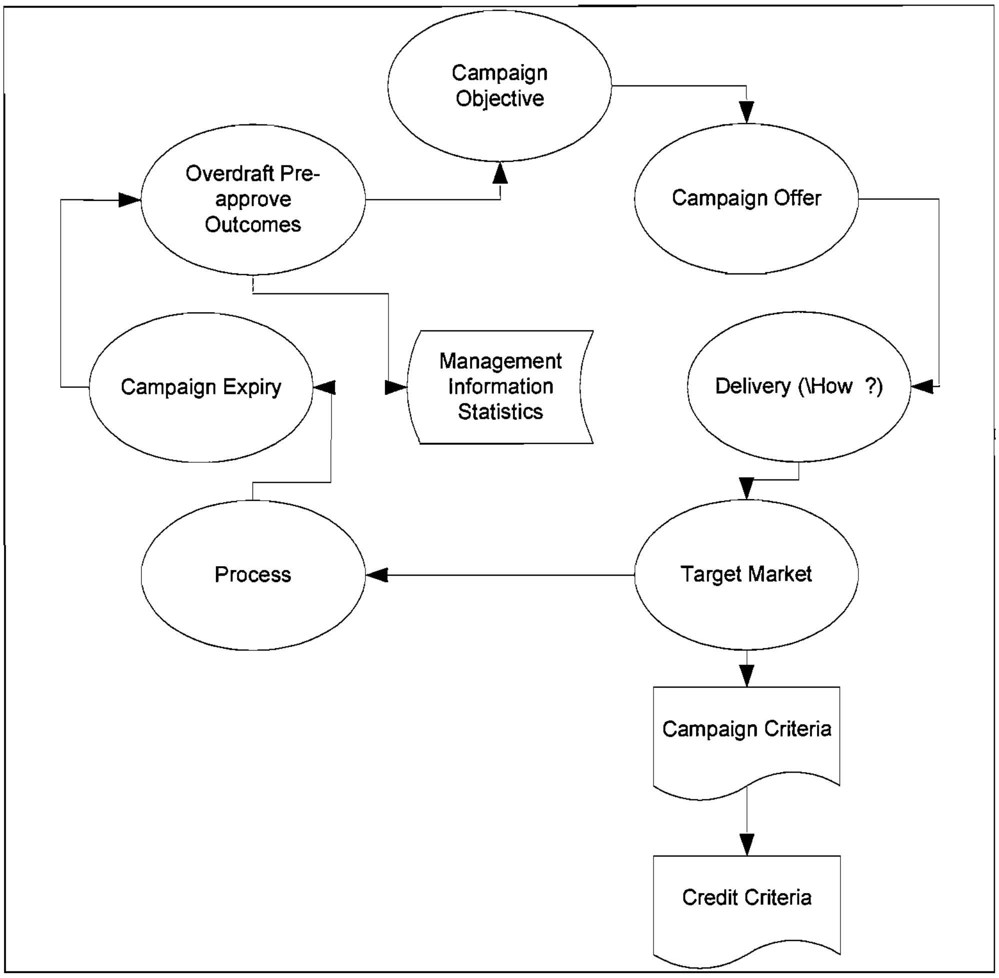


Figure 12: Campaign management flow diagram

Campaign management consists of the following:

- Objective, which provides the mission statement of the campaign. It will usually indicate whether or not the target population is composed of new or existing customers, the product that will be campaigned on, and the target market.

- Campaign offer, which states exactly what is offered to the customers, be it a limit increase, a new product, or an additional product.

- Medium, which specifies how the offer is to be communicated. Options include mailing (electronic or postal), telephoning, and physical interaction (invitations to events or interactions at the branch).

- Target market, which is the group to which the offer will be made. Its definition should be very specific, in terms of inclusion and exclusion rules.

  - Credit criteria: affordability and credit risk criteria should be used to exclude any customers that are prone to becoming overexposed, or who are already delinquent.
  - Acceptance criteria: what the customer has to do to accept or reject the offer must be stated, and the period of the campaign must be given.
- Campaign expiry: the expiration date and conditions for the campaign.

- Process flow
  - The collection of data to the thank-you letter to the customer are defined in the process flow section.

- Outcomes: negative and positive outcomes are defined, such as expected take-up percentages, reduction of risk, and increase in utilisation.
  - Data validation ensures that only the appropriate target market group has been included.
  - Management information statistics are required to measure the success of the campaign.

The approach for the challenger campaign entails calling the customers and offering a limit increase to them, at a fee (1000 customers), and mailing a letter stating that their limit has been increased, with the option to decline by phoning a toll-free help desk.

The simulation is based on the probability of the take-up of the offer, where the best case of take-up is 30%, the worst case of take-up is 1%, and the probable case of take-up is 10%.

### 4.4.2 Preventative measures (damage control)

It is important to keep in mind that the targeted population is existing customers of the bank, so the credit limit change should be as smooth as possible. Precautionary measures include ensuring that a customer does not have too many other product exposures and is in non-risky category, retaining a master list of customers and account numbers, and confirming campaign requirements and other monitoring criteria.

The data market is presented in the following section.

## 4.5 Defining the data mart for monitoring

The data-monitoring mart is comprised of the fields defined in Section 4.3 The following elements were included in the data mart used to monitor the strategies.

- Account number - each account has a unique identifying number, with a product number embedded in it and all account numbers for a given product fall within a given range;
- Customer segment - the market segment that the customer has been assigned. Examples are sole proprietors, retail individuals, and small medium enterprises;
- Customer risk grade - the classed credit score, produced by the credit decision engine;
- Average credit balance - end-of-day account balances are recorded, and credit balances are totalled and divided by the number of days the account is in credit during that month;
- Average debit balance - end-of-day account balances are recorded, and debit balances are totalled and divided by the number of days the account is in debit during that month;
- Average debit interest - the debit interest of the account is calculated by calculating the average debit balance for the month and subsequently calculating the interest incurred by the customer. Some systems have interest debit events that automatically calculate the interest incurred, thus a sum of this field would show the total debit interest. The interest is payable by the customer on debit balances. The average is then calculated for each of the challenger and champion groups.
- Average fee income - as with the average debit interest, the fee income is totalled for each account and averaged for the segment;
- Collection statuses - a frequency distribution is provided for the different collection status codes for each segment;
- Bad rates - the good/bad statuses are calculated as part of the scorecard monitoring, using the definition selected. The bad rate is calculated as the number of bad accounts as a proportion of the total in the sample/population;
- Take-up rates - this refers to the number of customers that accepted the offer, as a proportion of the total accounts used in the experiment;
- Call-centre complaint - the number and types of complaints made by the targeted customers.

In the last section, measures of success and failure are defined.

## 4.6 Defining measures of success and failure

This section defines success measures. Since the research project affects different areas, different measures are used in each. For this campaign, the following measures of success were used:

- a hit-rate comparable to other campaigns run by the department;
- minimal customer complaints; and
- the number of failed attempts to contact a customer.

The challenger strategy should not have a pronounced adverse impact on customers' credit risk profiles. At least initially, the challenger strategy should decrease the number of accounts over-utilising their limits, relative to the champion. The new limits may cause some customers to overextend themselves though, causing a net deterioration. The increased interest income generated by the challenger will may be sufficient to offset this.

## 4.7 Conclusion

Chapter 4 defined the measurement milestones, where a champion-challenger must be monitored at different milestones(immediate, interim and final) to ensure that the changes that have been made are generating the desired effect. Monitoring reports were defined, which will help stakeholders to gauge the effectiveness of the proposal. The methodology to simulate the process was defined and finally measures of success and failure was defined.

Chapter 5 will discuss the results of the simulation of the implementation, the physical process that was followed in the champion-challenger testing. The chapter contains the monitoring that was during the process and a period afterwards (to ensure that the change stabilises).

# CHAPTER 5: Research results and recommendation

## 5.1 Introduction

As described in chapter 4 and the research aim, the research project's objective is to target a portion of an identified segment with a new strategy.

The challenger was identified by the researcher during a quarterly scorecard development exercise, performed on the behavioural cheque scorecard. The full challenger population was identified based on their limit excess behaviour and facility (overdraft) utilization. To test the challenger population against the existing champion strategy, a smaller sample was selected.

The identified sample will be supplied to a customer call centre, who will contact customers, to offer them a new limit, calculated from their credit risk behaviour and credit turnover balances. The final list of customers who were accepted the offer were then be forwarded to the credit team, who changed the customer overdraft limits on the mainframe system. A test was performed the next day to ensure that the limits have been correctly recorded against the accounts.

As discussed in chapter 4, there are three different monitoring stages: initial, interim, and final. Because the initial and interim account behavioural measures reflect the same information over different periods, only the results are covered in Chapter 5. The call-centre information, stipulated as part of the initial measures, is only measured after completion of the call-centre exercise (which is once-off).

In this chapter, the results of implementation are presented and discussed in Section 5.2. Thereafter, the results of monitoring are presented and discussed in Section 5.3.

## 5.2 Implementation

The marketing team raised concerns regarding the potential loss in non-interest revenue (NIR), because of no longer charging these clients penalty fees. It was suggested that the clients be charged a R100 once-off 'administration fee' to try to make up the loss.

The initial sample size chosen by the researcher was 5,000 clients but because of the banking code of conduct perspective, the client value proposition team requested another 1,000 clients, who would be called and offered the overdraft facility, but at a cost of R100.

Those clients that could not be contacted would then be referred to the credit department, who would put them through the same process as the remaining 5,000 customers, who would have their overdrafts loaded without the R100 charge. They were sent a letter notifying them of the increase, and that if they did not wish to accept the offer, they could call the contact centre to have it reversed.

The contact centre was used for all inbound queries and limit decreases. They were given access to the retail credit manual assessment centre (MAC) intranet site, which enabled them to decrease the limits at the client's request. The centre was used to call the 1,000 clients. If they accepted, the centre used the retail credit MAC to load the limit. In addition, the client's details were also captured on a spreadsheet, so that the R100 fee could be debited to the account at a central location. As the contact centre, call agents that were not accredited to sell the overdraft assurance were required to pass the lead on to the assurance call centre that followed up on the leads.

In the next section, the results of monitoring are presented and discussed.

## 5.3 Monitoring

The initial monitoring results are given in this section. The outbound call statistics supplied by the contact centre are outlined in Table 8, Table 9 and Table 10 below.

Table 8: Contact centre statistics

| Records sent | Call attempts | Contacts | Total sales | Sales to contacts |
|---|---|---|---|---|
| **977** | **2,339** | **476** | **348** | **68%** |

Table 8 shows the contact centre statistics where from the 977 records that they received 2339 call attempts were made 476 contacts were made with customers and of the 476 348 customers took the offer, thus showing a 68% sales to contact ratio.

Table 9: Total sales (1000 sample)

| Overdraft increase only | Overdraft assurance only | Overdraft assurance & increase | Total |
|---|---|---|---|
| **112** | **25** | **211** | **348** |

The offer to the 1000 customers were to increase their overdraft limit and as a test overdraft assurance was offered to the same customer. From the 348 sales made shown in Table 8 211 customers accepted the full offer, 112 preferred the increase only and 25 customers took assurance on their existing overdraft as shown in Table 9.

Table 10: Values and volumes of overdraft increases

| Data set | Number increased (take-up rate) | Value of increases: | Average limit increase per client: |
|---|---|---|---|
| 5 000 mailing | 4,418 (88%) | +/- R20,000,000.00 | +/- R4,500 |
| 1 000 call | 323 (32%) | +/- R2,000,000.00 | +/- R6,000 |
| **Total:** | **4,741** | **R22,000,000.00** | |

Table 10 shows the two approaches taken namely a mailing campaign and a call campaign. The mailing campaign shows a higher take-up rate 88% compared to the 32% from the call campaign. The call campaign however generated additional income in the form of assurance.

It is relevant to note that a total of R32,000 in NIR was generated from the 1,000 clients called, which excludes R3,30 per month per R1,000 of the new facility generated due to the take-up of insurance To date, confirmed credit insurance sales converted 86% of assurance leads for this initiative. Furthermore, the credit insurance sales have raised a potential asset value of approximately R 2 million.

Table 11: System confirmation of limit changes made

| | Number of customers passed from contact centre | Number of customer limit increases made on the system |
|---|---|---|
| 5 000 mailing | 4,418 | 4,418 |
| 1 000 call | 323 | 323 |

Table 11 provides confirmation that limits were correctly changed on the system. The customers that were mailed, but did not take up the offer were not affected.

Table 12: Mail campaign costs

| Total number mailed | Cost per mailer | Total cost |
|---|---|---|
| 5,000 | R5 | R25,000 |

The following graphs depict the performance of the test, by comparing the champion and challenger results.

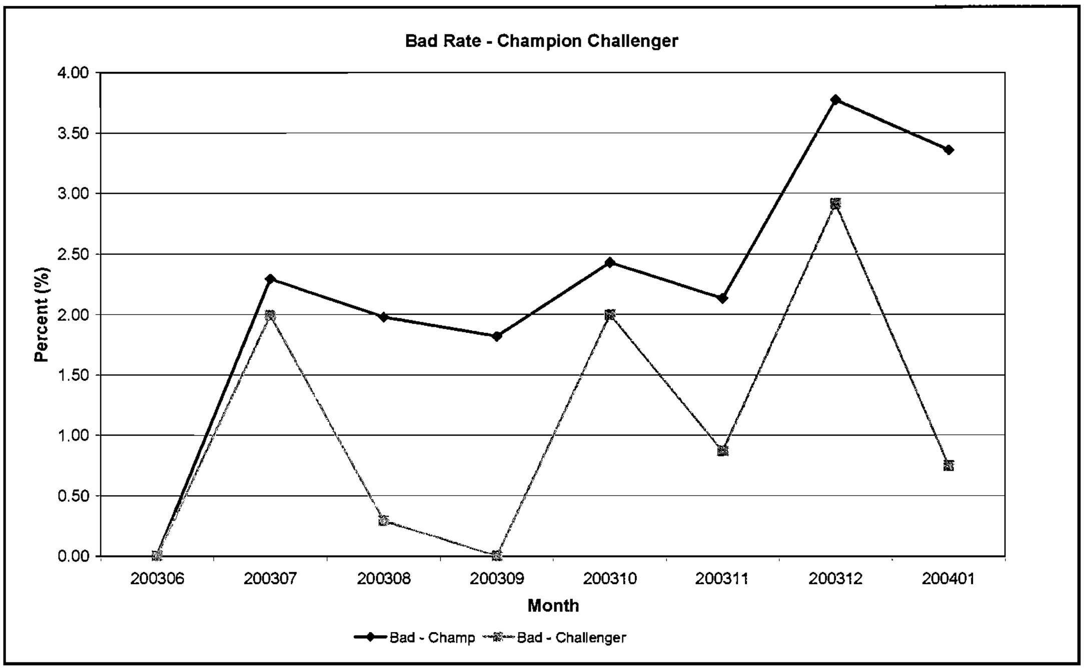


Figure 13: Bad rate

Figure 13 shows that on average the challenger's bad rate is 0.5% lower than the champion's bad rate. Section 4.5 defines bad rates as the good/bad statuses that are calculated as the number of bad accounts as a proportion of the total in the sample/population. The desired effect has thus been achieved, as the challenger's bad rate is not worse, but rather better. This is confirmed by the spread of Good/Bad/Indeterminates/Exclusions (GBIX) indicators shown in Figure 14, where it can be seen that the percentage of good accounts in the challenger population has increased.

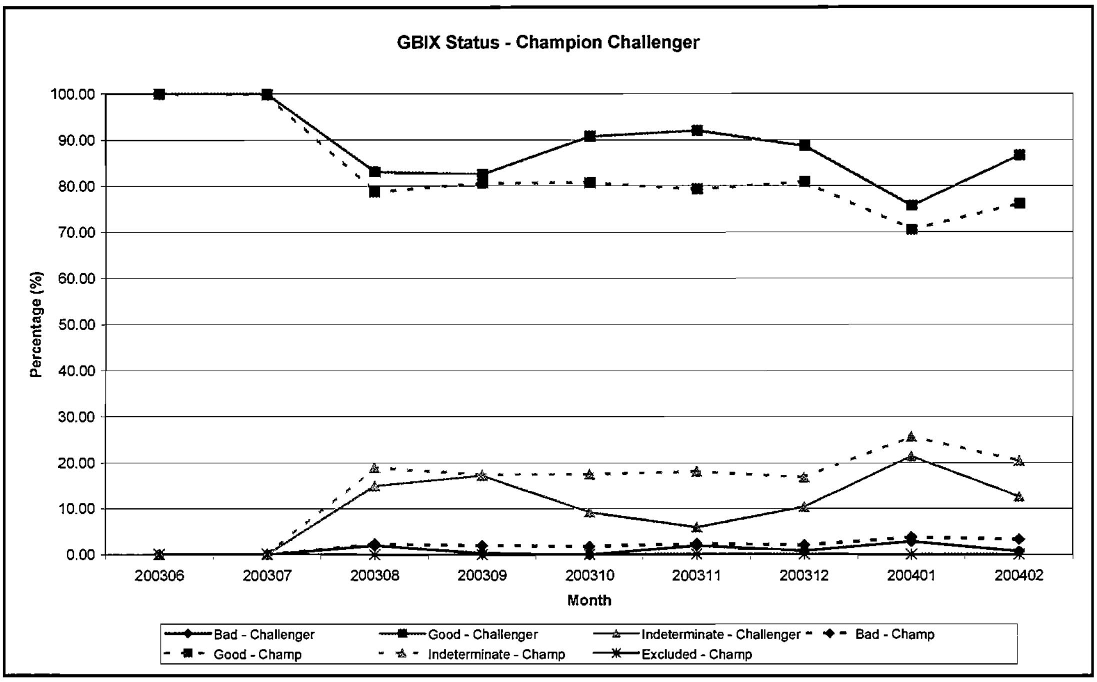


Figure 14: GBIX statuses

It is important to measure the collection statuses on the accounts, as this has a direct effect on the client and is another indicator of risk. Section 4.5 defines the collection statuses as a frequency distribution calculated for the different collection status codes for each segment. Figure 15 shows as the percentage of collections the challengers have recovered to a satisfactory status (blue dotted line extends to 100%), whereas the champion had a smaller recovery to satisfactory at times up to 10% less than the challenger (this is the difference between the dotted and solid blue lines, in month five). It is relevant that fewer challenger clients are entering an in-excess status, which is the desired effect.

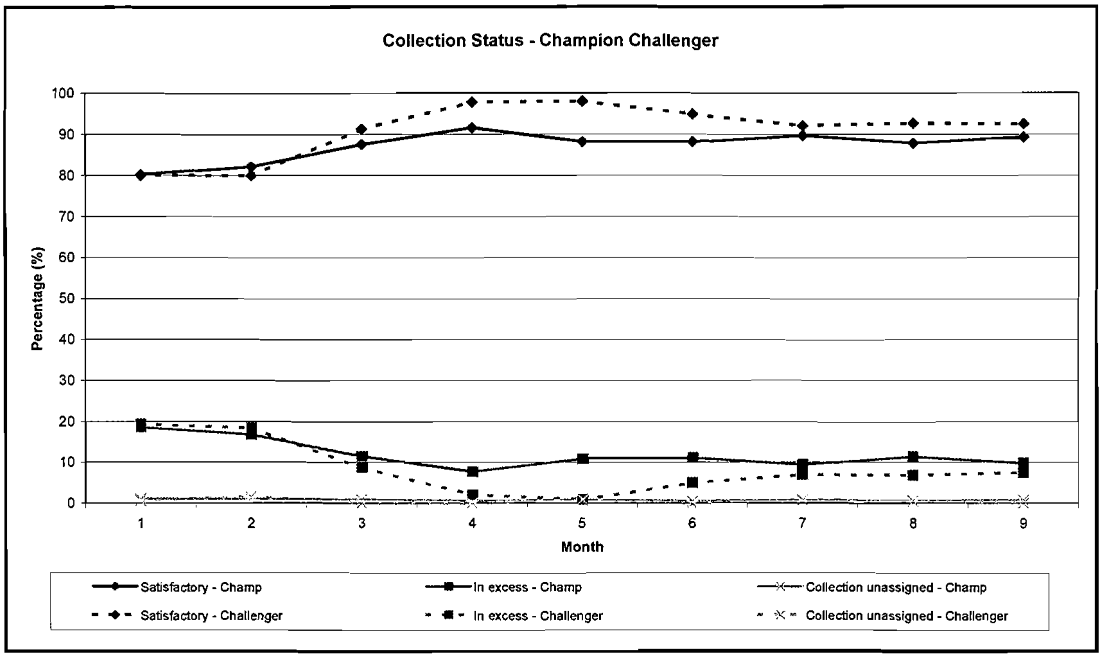


Figure 15: Collection statuses

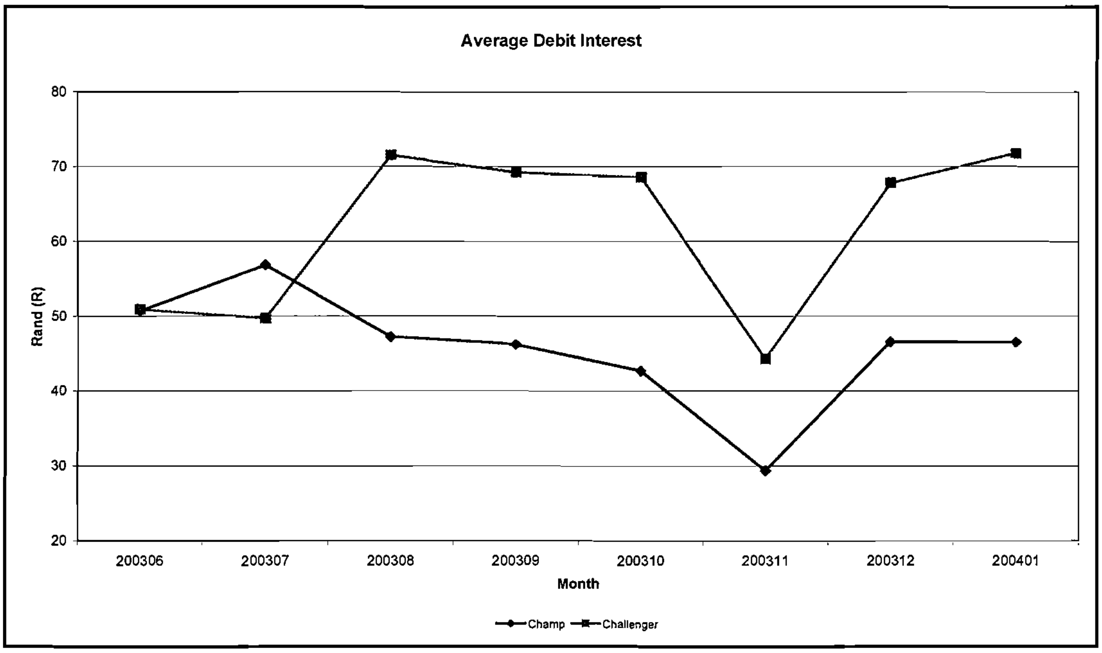


Figure 16: Average debit interest

Figure 16 indicates a significant increase in the interest paid by the challenger group, relative to the champion group. Section 4.5 defines the average debit interest as the debit interest of the account, calculated by calculating the average debit balance for the month and subsequently calculating the interest incurred by the customer. Some systems have interest debit events that automatically calculate the interest incurred, thus a sum of this field would show the total debit interest. The interest is payable by the customer on debit balances. The average is then calculated for each of the challenger and champion groups. This can be viewed as extra revenue to the bank. The increase in average debit interest is confirmed by the increase in average debit balances for the period, as shown in Figure 17, which is the result of clients in the challenger group making use of the increased facilities. Section 4.5 defines average debit balance as the end-of-day account balances recorded, and debit balances are totalled and divided by the number of days the account is in debit during that month.

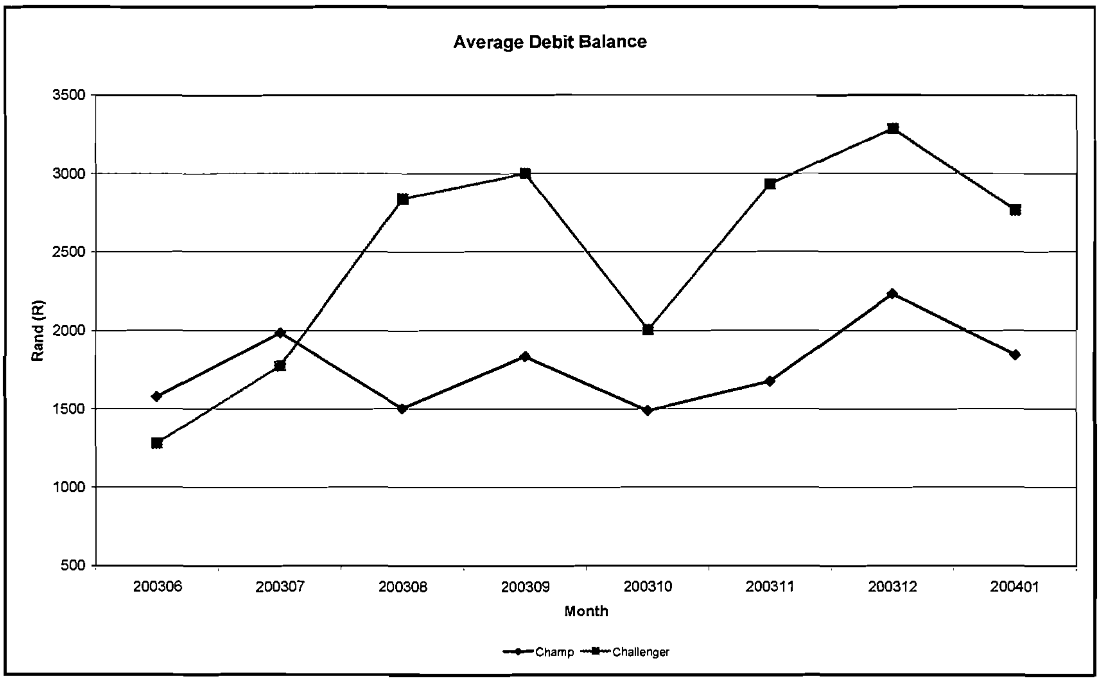


Figure 17: Average debit balance

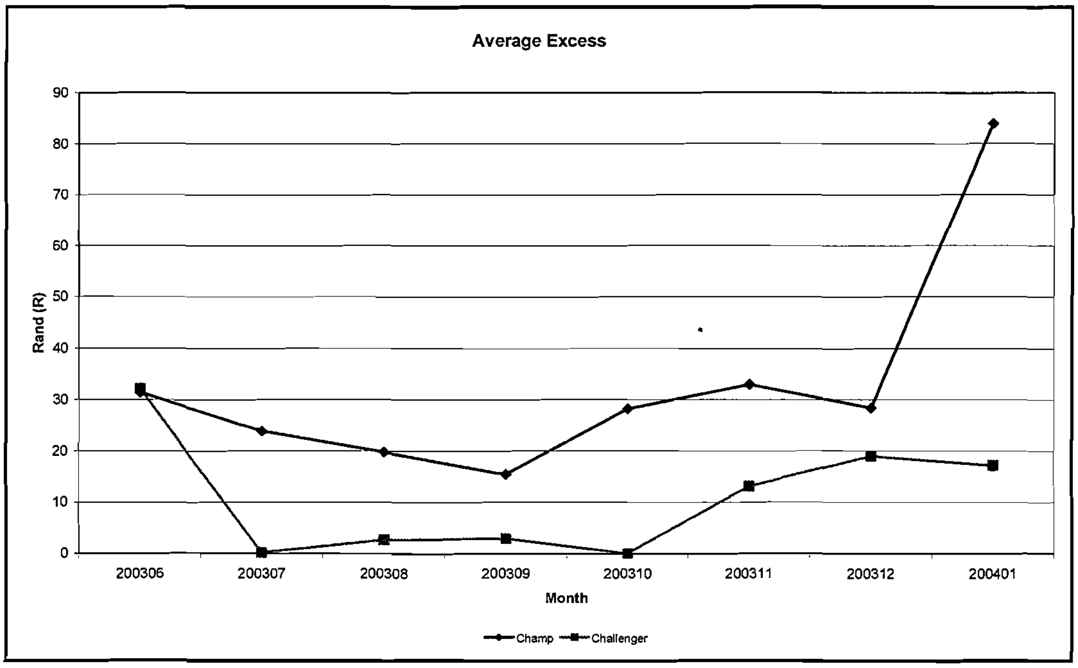


Figure 18: Average excess value

Figure 18 shows that on average approximately 25% of champion population is in excess, where the worst level recorded for the challengers over the same period is 20%. An account is deemed in excess its limit when the limit value has been exceeded by a transaction, which is seen as bad behaviour. The final month depicted in the graph shows an enormous increase, this could possibly be attributed to December seasonality.

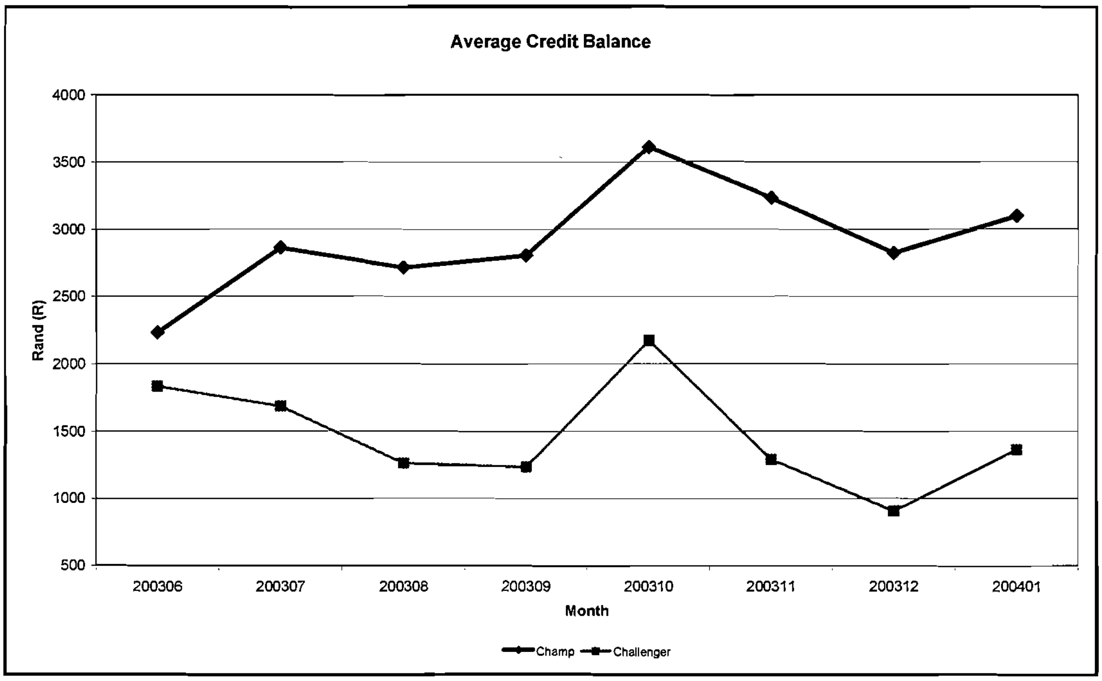


Figure 19: Average credit balance

Figure 23 shows that, as expected, the average credit balance for the challenger has decreased. In normal circumstances, the combination of reduced credit interest expense and increased debit interest income should lead to increased profits. This does, however, depend upon the interest rate paid upon credit balances, and the manner in which these funds are used elsewhere in the financial establishment. This should be considered as part of the evaluation.

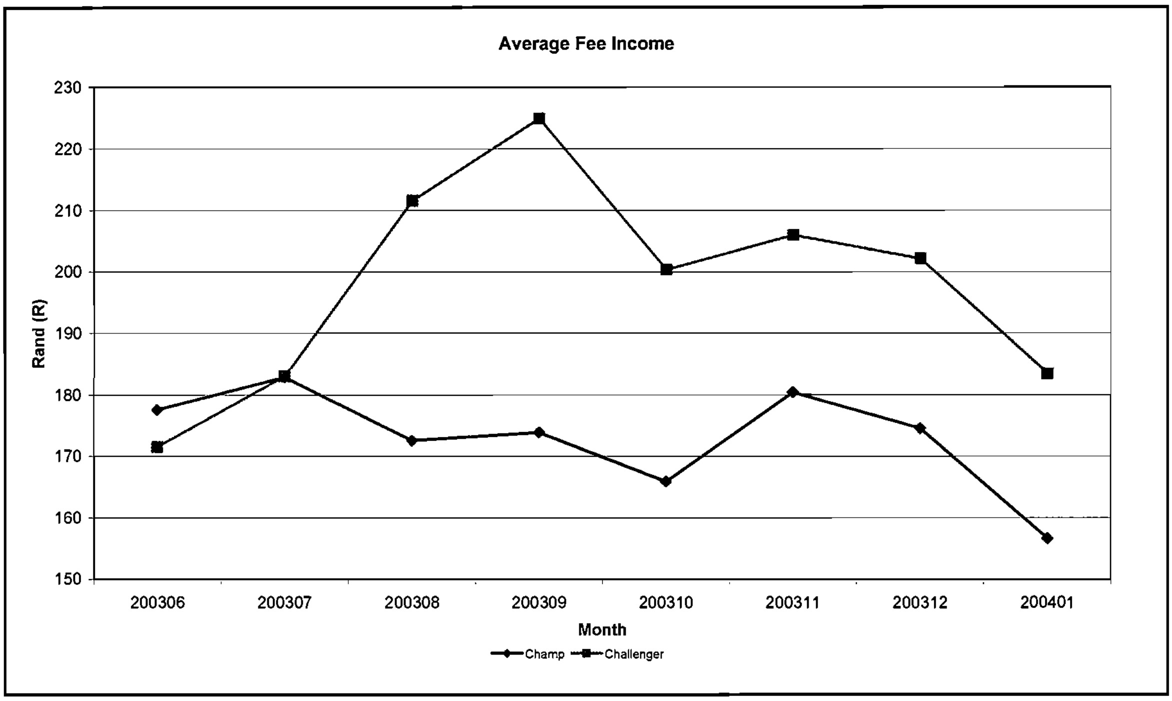


Figure 20: Average fee income

The average fee income from the challenger has increased by approximately R30 per account per month, as depicted in Figure 20. Section 4.5 defines average fee income as all fees posted on the account totalled for each account and averaged for the segment.

Based on the results given above, the challenger has performed well within the initial specifications, and can therefore be recommended for the rest of the base, possibly charging a fee for the service. The principle measures of portfolio performance at this stage might be a risk assessment, conducted by monitoring the changes in behavioural score distributions, and an assessment of the average debit balance increases.

## 5.4 Conclusion

Chapter 5 provide the results from the champion-challenger implementation and the test result in the form of monitoring graphs were provided. A decision to recommend the challenger strategy has been derived from the results.

Chapter 6 will provide a review of the implementation of the champion–challenger and discuss the lessons learnt from the implementation that can be applied to future implementations.

# CHAPTER 6: Review of the implementation and benefits thereof

## 6.1 Introduction

In Chapter 5 the implementation results were presented and discussed and recommendation was made to pursue the challenger strategy. According to Anderson (2007:116) champion–challengers are in the realm of adaptive control, which is a methodology applied within decision science. The concept of adaptive control is an enhancement of the feedback loop mainly found in electronics and engineering, and consists of the following steps:

- monitor: measure whether the process is working as intended;
- feedback: keep track of any errors/faults/deviations;
- identify: determine what caused the error; and
- control: based on findings change process appropriately.

Adaptive control is found in automated systems and is composed of the following:

- process: the application or strategy is working as defined;
- controller: ensures the process is running as intended by regulating it with predefined parameters;
- identifier: similar to feedback loop, but combines the monitoring and adds recommendations; and
- design: determines the changes to the process to adapt to anomaly; it is similar to the control part in the feedback loop.

Most lenders who can justify the cost by the volumes they process use consumer credit control systems. The concept of adaptive control is used in these systems as well where the controller is human-based and the decisions are based on the feedback from the identifier reports that are generated on anomalies. To put this in context, the scorecard monitoring reports serve as the identifier, the automated scoring of a customer based on parameters serves as the process and design, and the credit department resources, which use the monitoring output to identify underlying shifts and make recommendations as to what components of the process are to be addressed, serve as identifier parts.

In this chapter, strategy management is discussed in Section 6.2. Next, examples of champion–challenger implementations at the Fair Isaac Corporation and PIC Solutions are presented in Section 6.3. Following this, the benefits of the project are reviewed for both the bank and the customer in Section 6.4. Then in Section 6.5, the implementation is reviewed. Thereafter, the lessons that have been learnt are discussed in Section 6.6. Finally, recommendations for the future enhancement of a champion–challenger strategy are made in Section 6.7.

## 6.2 Strategy management

The most widely known strategy is that of a cut-off strategy in an application scorecard. The management of this strategy was be done by the monthly monitoring reports, which contain information on the decisions made by the automated system. Information items commonly associated with measuring the success of the cut-off strategy are divided front-end and back-end report information.

### 6.2.1 Front-end report information

Front end reports can be associated with the decisions being made by the credit scoring engine, that are monitored on a monthly basis, the first two measures below are specific to application scoring.

- scorecard adherence measured by the accept or reject rate;
- overrides and referrals;
    - high-side override: above the cut-off;
    - low-side override: below the cut-off;
- population stability; and
- characteristic analysis (McNab & Wynn, 2003:71).

If these measures indicate that, the scorecard decisions are not being adhered to further analysis should be done to identify the cause and be rectified.

### 6.2.2 Back-end report information (performance reports)

If any performance is available, back-end or performance reports can be constructed. Common measures include delinquency distribution reports and transition matrixes (Anderson 2007:493).

Behavioural scorecards are used to manage the performance of the book. Strategies associated with the management of behaviour are commonly found in transactional products, since they have limits associated to them. Usually most of these transactional portfolios are unsecured lending; thus, it is very important to track the behaviour of customers on an ongoing basis, to reduce losses. As with application, scoring monitoring should take place with the scoring cycle, as it helps to identify any shifts early, and appropriate action can then be taken.

As with application or origination, scoring account management has its own set of strategies. A common strategy in the account management realm is limit management. Other examples of strategies include no pay or pay decisions, where an accountholder is trying to pay for something that will use up and exceed the limit, a decision is made to pay it or decline the request.

McNab and Wynn (2003:208) list the following credit limit changes:

- solicited increases, in which a customer requests a credit limit increase;
- temporary excess, in which a customer's purchase exceeds declared limit but is lower than the shadow limit (limit calculated monthly that indicates the overall willingness of the bank to lend to the customer, but is not communicated to the customer); the limit is temporarily changed to allow the purchase;
- unsolicited increases, since the behaviour scorecards run every month a target limit is calculated. Should the customer comply with other behavioural criteria and the declared limit is lower than the target limit the customers limit is adjusted;
- credit limit decreases, decreasing the customers limit does not occur often but is used especially when dealing with customers that are not managing their arrears status.

Benefits for strategy management from implementing a champion–challenger are evident in the frequency of the review period associated with the strategy life cycle. Furthermore, as the population is shifting, a strategy will be updated, to manage the new challenges introduced by the shift. Strategies are dependent on more than the scores produced by the scorecard, other information includes the customer's income, which is used to set the limits in transactional products and determine the extent of the facility to be extended to customers who require a term loan (such as personal loans and home loans). Since contact is made with the customer, an opportunity arises to update the customer's information. Other ways of calculating the optimal limit to entrust to the customer can be tested.

In the next, examples of champion–challenger implementations are presented.

## 6.3 Examples of similar implementations

Prominent examples of the implementation of champion–challengers are mostly published by credit scoring consultancy firms worldwide. The reason for this is the amount of secrecy associated with a lender's scorecards and the strategies associated to the scores (Anderson, 2007:464). The examples discussed below were published by an American business consultancy firm, the Fair Isaac Corporation, and a local (South African) business consultancy firm, PIC Solutions.

### 6.3.1 The Fair Isaac Corporation

The Fair Isaac Corporation is a consultancy firm in the San Fransisco in the US concentrating on enterprise decision management. Their clients include:

- Nine of the top ten companies in the Fortune 500;
- Ninety-nine of the top 100 US banks and half of the top fifty banks in the world;
- Nine of the top ten UK banks;
- More than 400 personal and commercial lines insurers in North America and Europe, including nine of the top ten US personal lines insurers;
- More then 150 retailers;
- More then 100 telecommunications providers worldwide, including eight of the top ten US wire line telecommunications carriers and the top ten US wireless providers; and
- More then eighty government and public agencies. Fair Isaac Corporation (1993),

Bill Isaac and Earl Fair established the Fair Isaac Corporation in 1956. The Fair Isaac Corporation has played a fundamental role in the history of credit scoring as one of the first consultancies to implement an automated credit scoring system for a customer. The Corporation developed a solution for the systematic implementation of strategy changes, called *Strategy Science*, which has been implemented for a number of their customers (Tvenstrup & Goeller, 2003).

The following example is one of forty projects undertaken by the Fair Isaac Corporation in a period of two years. The solution's offer was strictly for credit line increase decisions, and the target was to obtain the optimal line amount change.

A bank has approximately 4 million member households in forty-two states in America. The majority of members of the bank are situated in rural areas. Of the 4 million member households the bank has approximately 100,000 managed credit card accounts. The particular bank purchased the current portfolio and converted it in August 1999. The first line management strategy was implemented in February 2000 on the credit card accounts. The management of this bank desires to improve account management strategies continually, and are faced with the following limitations:

- account management limitations, where that the target portfolio is small thus limiting champion–challenger testing;
- limited historical data of different credit limit increase strategies that were implemented historically;
- too few internal analytical resources to devote to this problem; and
- the portfolio size or revenue, which does not allow for costly custom projects (thus the optimised strategy was implemented on 50% of the portfolio as challenger).

Regardless of these limitations, a champion–challenger was successfully implemented, the results of which are discussed below.

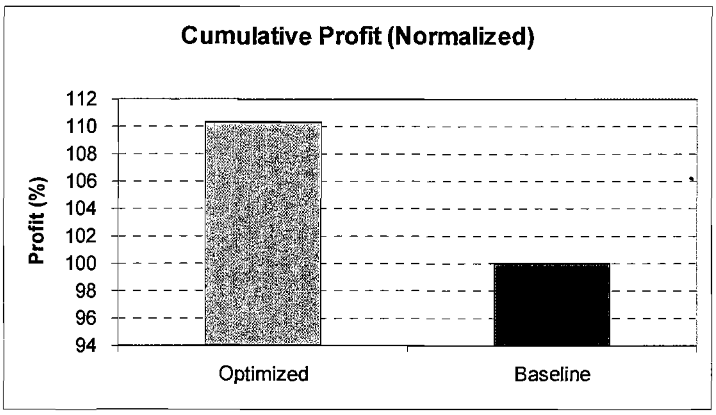


Figure 21: Cumulative profit after implementation of a champion–challenger (example)

The cumulative profit for the portfolio increased by 10%, if the challenger is compared to the base. The current balance growth was monitored for a period of nine months following implementation. It is important to monitor the progress of the challenger over such a period. Green (2003) from the Fair Isaac Corporation suggests that if the profit gain does not flatten out after eight months, the gap between the champion and the industry-wide policies is significant. As can be seen from Figure 22, the current balance growth was still significant in month eight, indicating that the gap was significant between the industry wide policies and what the bank is offering.

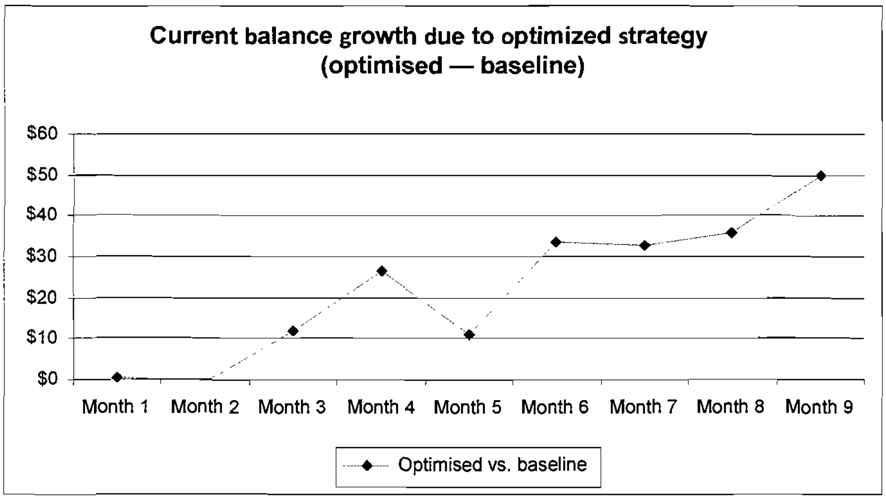


Figure 22: Current balance growth (example)

The benefit is thus clear in terms of balance growth and cumulative profit. A champion–challenger would be beneficial to implement where there has been a change in the economic environment and where the customers have different expectations from financial institutions. Customer satisfaction seems to be difficult to measure in studies like these. The best source for relationship information is the centralised help desk, where all complaints are logged. According to the Fair Isaac Corporation (1993), an increase in retention acceptance rates of 33% was obtained in a case study conducted by them. Further studies conducted by the Corporation (1993) indicated that through modelling the correct way the most profitable customers were retained on the book, without increasing the portfolio risk. An additional benefit of implementing a champion–challenger is that many lessons are learnt from the first implementation, which will improve any further implementations of a champion–challenger.

### 2.3.1 PIC Solutions

PIC Solutions is a South African based credit-scoring consultancy. They provide local and international credit scoring and optimisation consultancy.

A case study by Howard (2002) on a leading credit card issuer challenged the issuer's existing limit policies and strategies. The champion strategy was reactive and mostly customer initiated. Customers phoned the issuer for limit increases during peak seasons. The objective of the credit limit strategy is to increase sales and balances on good accounts, while minimising any increase in balances on bad accounts. The champion credit limit policy was reviewed with the operational overloads and risk factors mentioned in mind, to set the objectives for the challenger. The other objective of the business owner was to grant credit limit increases proactively to approved customers on regular intervals.

The challenger strategy had the following requirements:

- Accounts were to be assessed monthly for possible increased credit limits.
- Customers were to be granted credit limit increases every twelve months.
- Accounts had to be on the books for at least six months before an increase could be granted.
- A cut-off score was required to qualify for a credit limit increase.

The group selected for the testing of the challenger had the following attributes:

- low risk;
- high credit limit utilisation.

Customers with low credit limits received an incremental increase in their limit, and medium-high customers received a higher percentage of the calculated recommended limit.

Two groups of people were chosen from the total base with the attributes mentioned above, to measure the success or failure of the challenger. A 5% random sample was taken for both instances, and the groups were monitored over a period of a year.

The following account attributes were in the monitoring period:

- the average credit limit;
- the cumulative difference for finance charges;
- the customer's balance when it has been greater than four times in arrears to the balance in the current cycle as a percentage; and
- bad debt rate.

The results of the challenger credit limit increase strategy showed that both the finance charges and the sales increased compared to the champion, and bad debt levels were not increased. Other spin-off advantages mentioned were enhanced customer service and increased operational efficiency, caused by the decreased amount of manual inquiries for limit increases.

In Section 6.4, the benefits of the champion–challenger project presented in this thesis are reviewed.

## 6.4 The benefits of implementing a champion–challenger project

Banks are no different to retail companies in that they sell either a service or a product for a profit to their customers. The more they sell, the more they increase profit. Measuring benefit is thus quite simple: charge for a service delivered and determine the number of products sold. If there has been an increase since the previous period, an improvement has taken place and a growth in profit is declared.

Increasing the benefit to the bank and its shareholders could be as simple as charging more for services rendered and products sold. Considering a more reasonable approach, a customer's impression of the product or service determines the number of products or the amount of times that a customer would use the services offered. The costs of services and products should, therefore, be justified by their quality,. as similar services are offered by other vendors. The benefit of implementing a champion–challenger focuses on delivering an excellent service to the customer, with the by-product of an increase in profitability and retention without an increase in risk.

### 6.4.1 Benefits for the customer

Customer service is what makes the difference between one bank and another.

The benefits the customer will have are that there is a risk calculated limit assigned that manages the financial potential of the customer. Thus, the customer will, within reasonable bounds, not be exposed to a probable default. Another advantage to the customer is that the customer's portfolio will be analysed and possible areas of improved services will be highlighted through a champion–challenger. The benefit to the customer is interaction with the bank, where historically the bank was reactive to a customer's needs, it thus saves time on the customers' behalf.

Customers often use more credit than they have been allocated. Once a customer is in excess, they place the bank in a higher risk position, as the value of potential loss provided for is exceeded. It is thus imperative to train customers not to exceed their limit, by negative reinforcement, imposing a charge on the client for exceeding their limits. To run such an operation costs the bank money in monitoring, action, and collection fees. Customers have a negative perception of actions of this nature, because it usually has financial implications. The benefit derived is thus giving a customer ample low risk facilities, to avoid corrective actions taken by the bank, thus saving reputation risk, and lowering the volumes of customers entering the excess correction operation. There is obviously a loss in revenue in the operational section but reputation risk is saved, thus delivering a better service with the customer's needs central to the bank's commitment.

### 6.4.2 Benefits for the bank

A banking institution is exposed to many factors in the environment in which it operates. The benefits towards the bank based on the different environments can be seen in Figure 28.

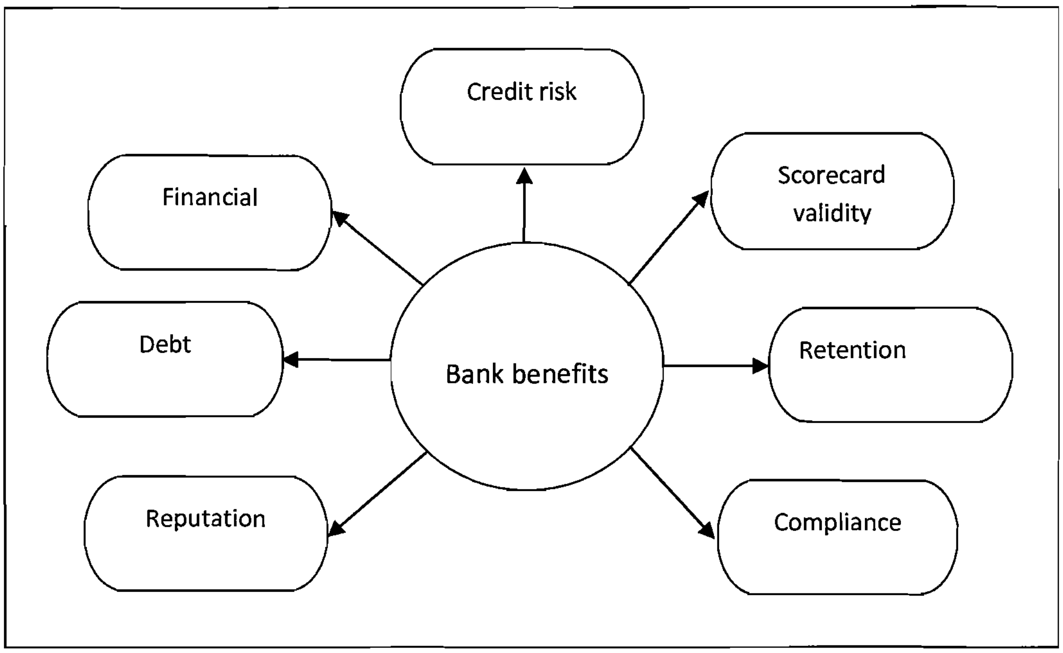


Figure 23: Benefits that the bank derives from a champion–challenger

Financial benefit

The benefits that are derived by the bank from a champion–challenger are in the extended exposure that the customer is given, the decrease in excess values (risk). Customers will move to better risk levels, as they will not have the negative information connected to their names, which in turn will help reduce the capital to be carried by the bank for riskier groups. The bank derives benefit from the opportunity to talk to the customer; other banking issues or possible expansions can be addressed through this interaction. As customers utilise the facilities granted, profit per customer rises, thus adding financial benefit for the bank.

Credit risk: decision support systems

The purpose of a challenger is to improve or at least not deteriorate the quality of the portfolio's risk and increase the profitability of the sample. The aim is, thus, to optimise the profitability curve of the customer product base to such an extent that the potential revenue risk does not deteriorate, caused by clients defaulting when over-utilising (exceeding) their credit limits.

Reputation risk

The other benefit to the bank has been mentioned under customer benefits in terms of excess management, where the benefit to the bank is in reputation risk saving through corrective actions taken towards offending customers. Therefore, it is imperative that these activities are monitored, to calculate the possible impact on revenue lost through collection fees.

The success of the challenger is dependent on the utilisation of the customers' limits, as interest charges are derived by facilities used by customers. The other advantage to the bank is the service fees that can be derived through customer paying with cash, credit cards, or cheques.

Compliance

As the customer relationship management is dependent on the changes in customers' needs and wants, customer credit management is dependent on the change in customers' credit spend. These changes are not only dependent on the customer's needs, but also on the economic environment, which arguably drives the needs of the customer. The scorecard monitoring will ensure the bank's models are performing as intended, thus ensuring that the capital for the bank is calculated on an optimal basis.

Economic changes

Examples can be seen when the interest rate drops and customers have a greater ability to acquire new credit-related goods. Lower interest rates create a greater spend capability of a customer, and move the total credit population in the risk bands. If the change in interest rates were drastic enough it could render a scorecard unpredictable, for example the rate hikes experienced by Zimbabwe.

Other factors that are likely to influence credit decisions, are the offers made by other banks to the client (an example is mortgage originators). If another bank has a better offer, it is obvious that they will attract more customers. The bank's current portfolio will drive application credit decisions; risk appetite and margins would have to be reconsidered.

Customer retention

It is cheaper to retain a customer than to attract a new one. This much has become accepted commonsense, especially because banks know which customers are adding the most profit to their bottom line, which means that resources could be focused on them (SAS, 1998).

Debt collection

Changes in customer behaviour and the economic and market environments cause clients to default on their commitments to the bank. Because of volumes, the bank employs information technology-driven solutions to aid in debt collection. The customers are treated according to their risk grade in the collection system. This enables different strategies to be followed for every risk grade. If a customer is labelled a high-risk customer, the customer will be handled differently. Tolerance in terms of corrective measures is built into collection strategies, which would hand over a defaulted customer in a far shorter space to the attorneys, than would be the case with a low-risk customer.

Scorecard validity

Scorecard monitoring helps with the identification of changes in the market. The score performance reports use the Gini co-efficient, to enable monitoring of how well the scorecard is performing. This report compares the score distributions of good accounts and bad accounts. It displays the performance of accounts over a fixed period, such as twelve months. This report verifies that the model is still ranking risk on a population of accounts. The expected distributions come initially from the scorecard development forecast, but may be updated later.

According to Thomas (2000), behavioural scoring models split into two approaches: credit scoring methods and probability models of customer behaviour. The bank in this research project uses behavioural scoring models, to score customers, achieve optimal credit lending methodologies, and derive probability models from the score results, to comply with the Basel II Accord requirements for holding the correct amount of capital based on the risk associated with the facility granted. Obtaining the optimal credit limits for customers based on risk and probability of default is therefore imperative for future banking, because of risk and the ability to price according to risk (positive or negative).

The use of a champion–challenger adds a benefit to a scorecard in the sense that it keeps the scorecard up to date with economic and market environment changes. Monitoring for a potential champion or challengers is a determining factor in the success of the application of a behaviour scorecard. The benefit of updating strategies continuously is for both the bank and the customer.

The following section reviews the champion–challenger implementation of this research project.

## 6.5 Review of the implementation

Considering that automated scoring was only introduced by South African banks in the mid- to late 1990s, the field of in-house scorecard development and strategy management is relatively new. The specific bank in the implementation of a champion–challenger of this research project has only used behavioural scoring since 1999, and there has been no active management of the strategies since implementation.

Section 6.6 shows the success from the example in this study.

## 6.6 Example demonstration

The example in the study shows a number of important steps in order to make a success of a strategy champion-challenger experiment. These steps include:

- perform periodic scorecard and strategy monitoring;
- identification of an opportunity;
- arrange a start-up meeting to introduce the opportunity to stakeholders;
- obtain sign-off to proceed with the experiment;
- document the process to be followed and assign tasks to project team members;
- define sample size from original findings and extract the sample;
- define campaign strategy to be followed;
- define the measures of success and failure;
- define the monitoring/tracking database based on the defined measures;
- implement the optimised changes to the sample;
- monitor the sample on a monthly basis; and
- document the findings from the monitoring exercise with recommendations.
-

The success of the experiment can be seen from the following:

- scorecard and strategy monitoring schedule and template established;
- buy-in from stakeholders and project members; and
- contribution per account

The schedule and template developed for scorecard and strategy monitoring will enable future identification of champion-challenger opportunities to be investigated. If a bit of effort is made to automate most of the scripting and reporting further reports can be generated, the time between monitoring can be shortened to enable quicker response to changes

It is extremely important to have buy-in from stakeholders, as well as the project team. The success of the experiment depends not only on the analyst who identified the opportunity but the delivery of every person involved in the process.

The average fee income per account has risen from R155.00 to R185.00 (based on the last monitored month) for the sample of 4741 that have taken up the offer, additional non-interest income of R142,230.00 on average generated per month. If the challenger strategy were implemented to the total base, the possible increase in revenue would be astronomical. Considering the number of times challenger strategy customers breached the agreed limit (in excess) compared to the champion strategy customers, shown in Figure 18, one can draw the conclusion that the challenger strategy customers is not increasing the credit risk of the portfolio, and is actually performing marginally better that the champion strategy customers.

The lessons that have been learnt from the implementation, which can be applied to future implementations, are discussed in the next section.

## 6.7 Lessons learnt from this implementation

The decision support area was able to identify a potential group of customers to target with the experiment. There is, however, a challenge to try to automate the champion–challenger testing process, by using the constraints identified, to select the experimental population.

The existing infrastructure presented hurdles, since controls were in place ensuring that only a certain number of account limits could be modified at a time. The user had to have an extremely high level of clearance to make the changes. The successful implementation, however, proves that with some ingenuity, innovative ways can be found to implement the solution automatically.

In terms of campaign management, two communications approaches were taken:

- Calling the customers with an offer of a new limit:
    - The customer's limit would be increased if a fee of R100 was paid.
    - The opportunity was used to sell insurance to the customers.

- Customers were notified by mail of the new limit allocated to them and only if the customer did not want to take up the offer was action required from the customer.

The take-up rate proved to be greater for the customers that were notified through the mailing campaign, because the customers were given the opportunity to opt out. The client call-centre campaign produced some non-interest revenue, which covered the cost of the campaign. In the longer term though, the net interest earned from the higher borrowings should overshadow the NIR.

Relationships between marketing and credit have always been a point of contention. Indeed, just the idea of charging the customer a fee for increasing the limit, and using the opportunity to sell credit insurance could be a point of contention. It can, however, safely be said that the mail campaign was relatively straightforward, and should provide better results in the long term.

Finally, in the following section, recommendations for the future enhancement of a champion-challenger strategy are suggested.

## 6.8 Enhancements to be considered

The research project focused on implementing a recommended limit, based on the risk score and the facility (overdraft) utilisation and limit excess behaviour. As can be seen from the current balance, limit utilisation, behavioural score, and current limit were used to calculate the recommended limit. These relationships can be stated as mathematical relationships, and the recommended limit can be optimised.

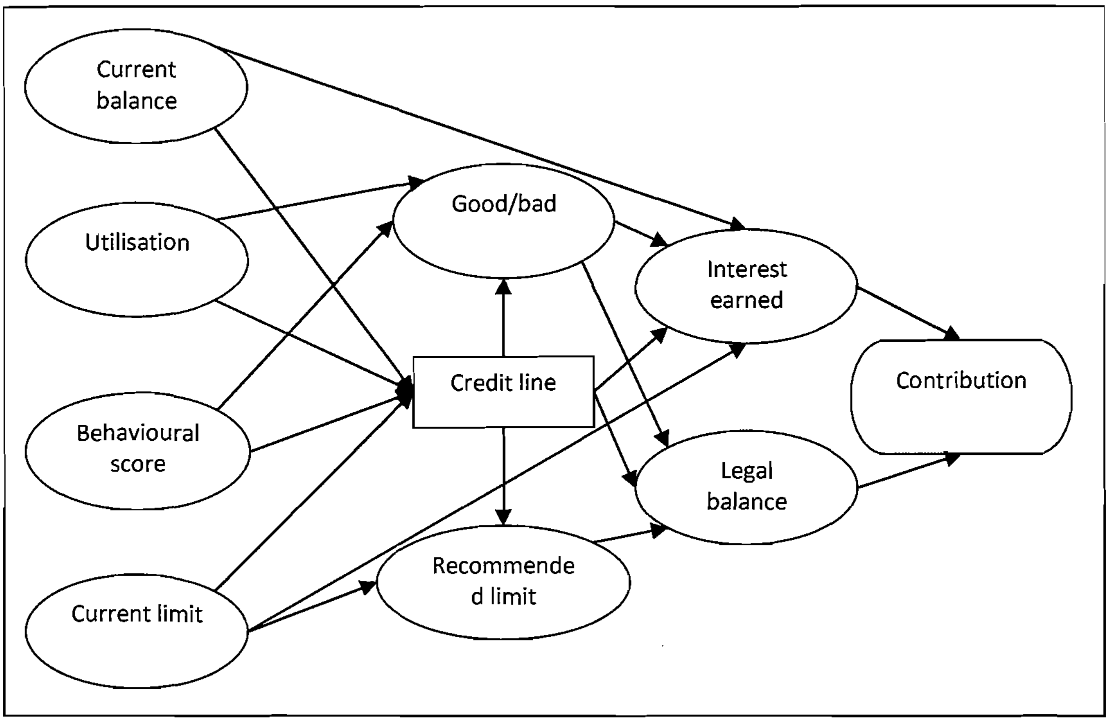


Figure 24: Bank actions and client reactions model

Oberstein (2003) from the Fair Isaac Corporation suggests that one model any actions that could be taken to improve the profit from the customer. Once the graphical model is completed, the mathematical relationships are defined. With the mathematical relationships between actions and reactions, optimised profit can be modelled. Thus, one wishes to have an optimal risk/return trade-off, using the limit as a tool. As can be seen from Figure 25, inputs such as the bureau score and attrition score can be used. The mathematical technique suggested by Oberstein (2003) is neural inference, which infers the optimal value for the customer's communicated limit. Other mathematical and statistical methodologies that could be used are mathematical goal programming and linear programming. If all the relationships are defined mathematically, they can be used as constraints with which to optimise the communicated limit.

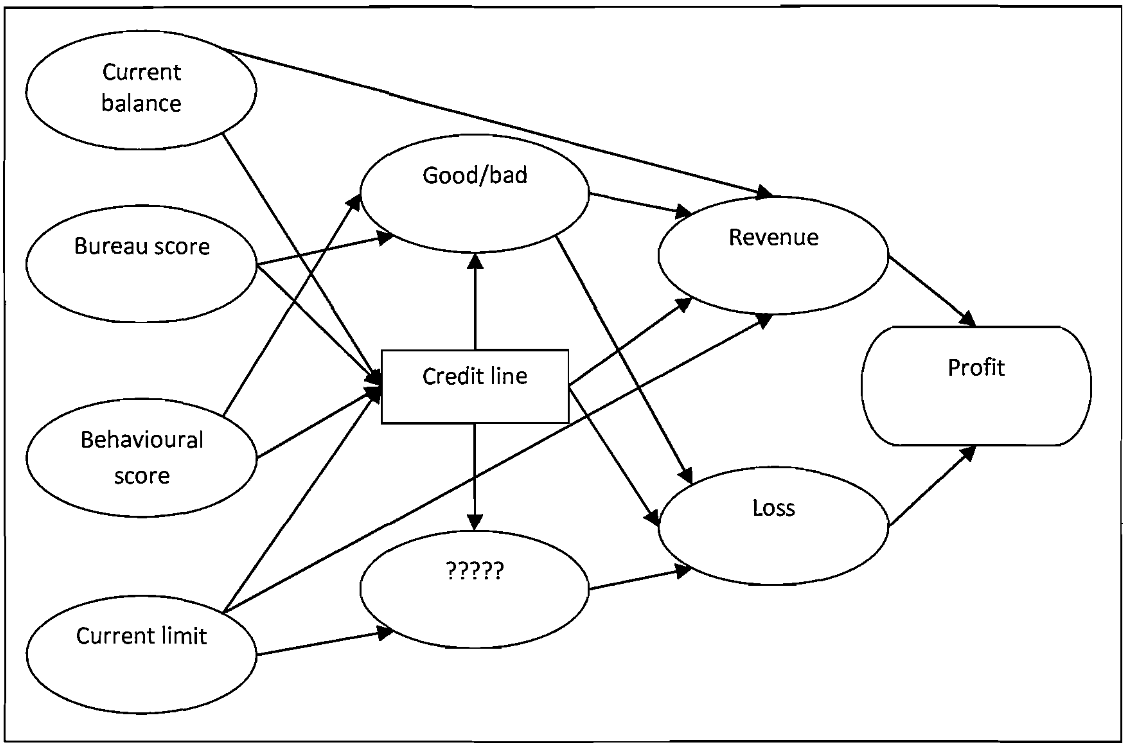


Figure 25: Customers reactions to bank actions graphical model

## 6.9 Conclusion

According to Love (2002:2), even the best risk management strategies require constant challenging, to ensure that they are performing optimally. As populations shift and operating and economic conditions change over time, a lender's account base will react or behave differently in response risk management strategies. Additionally the objective of risk management strategies is to alter or change account holders' behaviour over time; as such, it is critically important that the strategies deployed by lenders continue to reflect the changed behaviour of the customer base. Champion–challenger testing is a process through which lenders can implement and 'test' alternative strategies in a controlled manner within the 'live' environment.

The chapter has listed a number of possible benefits, which can be gained by implementing a competing strategy. Two industry-related examples have been given, and the benefits derived by the projects have been listed. Furthermore, the chapter has given a background to the different scorecards and a brief description of their functions.

The experiment proves that it is possible to test strategies, and that doing so will improve profits. Furthermore, customer relationships will be enhanced if good credit behaviour is rewarded. Rather than earning revenue from penalty fees, the focus instead shifts to interest income derived from use of the increased facilities.

Scorecard development and monitoring still needs to be performed on an ongoing basis, as the greater the experimentation, the shorter the period over which the scorecard will be valid, because it makes the base assumption that the future will be like the past even less valid. Given that the customer, the bank, and the decision support areas have gained in some fashion, the experiment proved to be well accepted by the bank's strategic management team, who planned to do further similar experiments in future.

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