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**Original Citation**

Abdou, Hussein (2006) Credit risk in Egyptian banks. In: Proceedings of the Plymouth Business School and School of Sociology Politics and Law Postgraduate Symposium 2006. University of Plymouth, Plymouth, UK, pp. 107-127. ISBN 1-84102-151-2

PROCEEDINGS OF THE PLYMOUTH BUSINESS SCHOOL AND SCHOOL OF SOCIOLOGY, POLITICS AND LAW POSTGRADUATE SYMPOSIUM 2006. 

# CREDIT RISK IN EGYPTIAN BANKS

Hussein Abdou

## Abstract

*This research aims to identify the currently used techniques in evaluating credit risk in Egypt's banking sector, then to evaluate these techniques and to develop model(s) to evaluate credit risk in Egyptian banks. In a pilot study, the researcher conducted informal interviews with key personnel in three of the Egyptian banks, in order to evaluate credit risk policies.*

*The pilot study showed that these banks do not use any of the statistical techniques in the evaluation process. So, the researcher expects that there will be differences between the existing techniques and the proposed techniques in terms of the results of the evaluation process, which will be reflected in the prediction ability in the future, after the implementation of the proposed techniques. At the final stage of the research an investigation will be conducted, by means of a questionnaire survey of Egyptian banks, into attitudinal aspects of implementation of sophisticated techniques. Logistic regression will be run in order to attempt to establish any significant link between the degree of predisposition to implementation and other banks characteristics, for example, size and number of branches.*

## Introduction

Nowadays, credit risks have become one of the most important financial topics of interest, especially, in the banking sector. The role of credit risks has changed dramatically over the last ten decades, from passive automation to a strategic device.

Risks are uncertainties resulting in adverse variations of profitability or in losses. In the banking universe, there are a large number of risks. Most are well known. However, there has been a significant extension of focus, from the traditional qualitative risk assessment towards the quantitative assessment of risks, due to both evolving risk practices and strong regulatory incentives. The different risks need careful definition to provide sound bases serving for quantitative measures of risk. As a result, risk definitions have gained precision over the years.

**Banking risks** are defined as adverse impact on profitability of several distinct sources of uncertainty (Figure 1).

Credit risk is the first of all risks (see: figure 1) in terms of importance. Credit risk is critical since the default of a small number of important customers can generate large losses, potentially leading to insolvency, (Bessis, 2003).

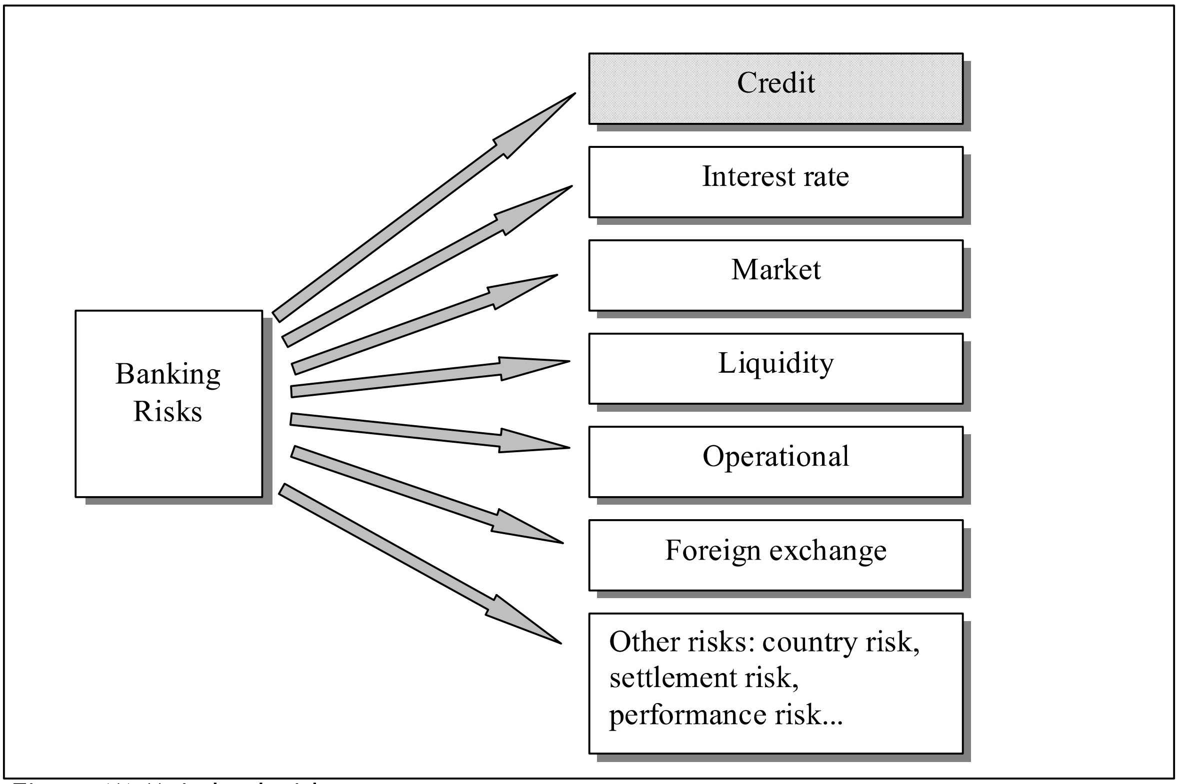


Figure (1) Main bank risks
Source: (Bessis, 2003), p.12.

Credit risk is the potential loss in the event of default of a borrower, or in the event of deterioration in credit standing.
In this research the term of "default" will be used a lot. Default risk is the probability of the event of default. There are several possible definitions of "default":
missing a payment obligation for a few days, missing a payment obligation for more than 90 days, filing for bankruptcy, restructuring imposed by lenders, breaking a covenant triggering a cross-default for all lenders to the same entity. It depends on the default definition, (Bessis, 2003).

**Modern banks** in all the world need to reduce their risks. Risk may be defined as the volatility or standard deviation (the square root of the variance) of net cash flows of the firm, or, if the company is very large, a unit within it. In a profit-maximising bank, a unit could be the whole bank, a branch or a division. Furthermore, risks specific to the business of banking are:

- **Credit**
- Counterparty
- Liquidity or funding risk
- Settlement or payments risk
- Market or price risk, which includes
    - currency risk

    - interest rate risk
- Capital or gearing risk
- Operational risk
- Sovereign and political risk, (Heffernan, 2005).

This research will focus on the first type of risks, which is credit risk.
Banks accept risk in order to earn profits. Credit risk is the risk to earnings and capital that an obligor may fail to meet the terms of any contract with the bank. It is usually associated with loans and investments, but it can also arise in connection with derivatives, foreign exchange, and other extensions of bank credit. Although banks fail for many reasons, the single most important reason is bad loans. Banks, of course, don't make bad loans. They make loans that go bad. At the time the loans were made the decisions seemed correct. However, unforeseen changes in economic conditions, and other factors such as interest rate shocks, changes in tax laws, and so on, have resulted in credit problems. Credit risk is the primary cause of bank failures, and it is the most visible risk facing bank managers, (Gup and Kolari, 2005).

Therefore, the process of credit risk evaluation has the interest of many researchers nowadays. [Recently, bankers have come to realise that banking operations affect and are affected by the natural environment and that consequently the banks might have an important role to play in helping to raise environmental standards. Although the environment presents significant risks to banks, in particular environmental credit risk, it also perhaps presents profitable opportunities, (Thompson, 1998)].

Banks must evaluate the ability of their customers to repay their financial obligations according to the agreement established between the respective parties. This evaluation process can be carried out using a credit scoring model, which is one of the most important and critical models in this area. Regarding consumer credit risk, people today take credit scoring for granted. It seems obvious that models to assess creditworthiness should be used and yet it was not that long ago that more widespread acceptance was achieved, (Bailey, 2001).

Credit risk in Egyptian banks is a growing area and the focus of this research, of which the main thrust is to develop a model to evaluate credit risks in the banking sector in Egypt.
A credit scoring model [see for example: (Lewis, 1992); (Bailey, 2001); (Mays, 2001); (Thomas,*et al.*, 2002); (Mays, 2004); (Thomas,*et al.*, 2004); and (Bluham,*et al.*, 2003)] is one of the most successful applications of research modelling in finance and banking, and the number of scoring analysts in the industry is constantly increasing. Yet because credit scoring does not have the same glamour as the pricing of exotic financial derivatives or portfolio analysis, the literature on the subject is very limited. However, credit scoring has been vital in allowing the phenomenal growth in consumer credit over the last four decades. Without an accurate and automatically operated risk assessment tool, lenders of consumer credit could not have expanded their loan books in the way they have, (Thomas,*et al.*, 2002).

**Credit scoring** techniques assess the risk in lending to a particular consumer. One sometimes hears it said that credit scoring assesses the creditworthiness of the consumer, but this is an unfortunate turn of phase. Creditworthiness is not an attribute of individuals like height or weight or even income. It is an assessment by a lender of a borrower and reflects both the circumstances and the lender's view of the likely future economic scenarios.

**Credit scoring** was one of the earliest financial risk management tools developed. Its use by U.S. retailers and mail-order firms in the 1950s is contemporary with the early applications of portfolio analysis to manage and diversify the risk inherent in investment portfolios. Also, credit scoring could claim to be the grandfather of data mining because it was one of the earliest uses of data on consumer behaviour.

**Credit scoring** is the set of decision models and their underlying techniques that aid lenders in the granting of consumer credit. These techniques assess, and therefore help to decide, who will get credit, how much credit they should get, and what operational strategies will enhance the profitability of the borrowers to the lenders [see for more details: (Long, 1973) and (Thomas,*et al.,* 2002)].

**Regarding the history of credit scoring**, this is only 50 years old. During the 1930s, some mail-order companies had introduced numerical scoring systems to try to overcome the inconsistencies in credit decisions across credit analysts. Credit scoring is essentially a way to identify different groups in a population when one cannot see a single characteristic that defines the group but only related ones. The first approach to solving this problem of identifying groups in a population was introduced in statistics by Fisher, 1936.
In the 1940s, Durand was the first to recognize that one could use the same techniques to discriminate between good and bad loans. It did not take long after the war ended for some folks to connect the automation of credit decisions and the classification techniques being developed in statistics and to see the benefits of using statistically derived models in lending decisions. The first consultancy was formed in San Francisco by Bill Fair and Earl Isaac in the early 1950s. During 1960s, the first arrival of credit cards made the banks and other credit card issuers realize the usefulness of credit scoring. The event that ensured the complete acceptance of credit scoring was the passage of the Equal Credit Opportunity Acts and subsequent amendments in the U.S. in the 1970s.
In the 1980s, the success of credit scoring in credit cards meant that banks started using scoring for other products, such as personal loans, while in the last few years, scoring has been used for home loans and small business loans.
During the1990s, growth in direct marketing led to the use of scorecards to improve the response rate to advertising campaigns. In fact, this had been one of the earliest uses in the 1950s.
At present, the banks' emphasis is on changing the objectives from trying to minimize the chance a customer will default on one particular product to looking at how the firm can maximize the profit it can make from that consumer, (Thomas,*et al.,* 2002).

**Judgemental techniques versus credit scoring techniques:** The overall idea of the application of credit assessment is to compare the characteristics of an applicant with those of past applicants whose repayment history has been observed. If an applicant's characteristics are sufficiently like those of people who have been granted credit, and have subsequently defaulted, the application will normally be rejected. If the applicant's profile is sufficiently similar to those of people who have not defaulted, the application will normally be granted. In general, there are two techniques which can be used:

- loan officer's subjective assessment, and
- credit scoring (the main interest of this research).

**Comparison between a judgemental system and a credit scoring system**: was discussed by Altman (1981) as follows:
In a judgemental risk evaluation system, each credit application and the information contained therein are evaluated individually by an employee of the creditor. The success of a judgemental system depends on the experience and common sense of the credit evaluator. Otherwise, in a credit scoring system: some creditors have used their historical experience with debtors to derive a quantitative model for the segregation of acceptable and unacceptable credit applications. With a credit scoring system, a credit application is processed mechanically and all credit decisions are made consistently. The scoring system is based on the addition or subtraction of a statistically derived number of points relating to the applicant's credit score on the basis of responses given to a set of predictor variables, such as time on a job or the number of credit sources used. Given a statistically derived cutoff credit score, a creditor can thus segregate the acceptable from the unacceptable credit applicants.
On the other hand, credit scoring has been criticized because statistical problems with the data used to derive the model frequently violate the assumptions of the statistical technique used to derive the points, Altman (1981). It is also pointed out that some of the variables used in a credit scoring system may have the effect of social discrimination, although to the statistician the variable may appear to be neutral. Finally, the credit scoring model is derived by analysis of the characteristics of the customers who were once granted credit by the creditor for whom the system is derived. The characteristics of the part of the population to which the credit grantor has not granted credit are not directly considered. Thus the scoring system may provide biased results when it is applied to new credit applicants.
Despite the criticism of credit scoring models, these models can be regarded as one of the most successful models used in the field of business and finance.

**Benefits of credit scoring:** credit scoring techniques have a number of benefits relative to judgemental techniques for both the lender and borrower:
Credit scoring requires less information to make a decision than does judgemental assessment, because credit scoring models have been estimated to include only those variables which are (statistically) significantly correlated with repayment performance; whereas judgemental decisions, prima facie, have no statistical significance and so no variable reduction methods have been used. Credit scoring models attempt to correct the bias that would result from considering the repayment histories of only accepted applications and not all applications. They do this by inferring how rejected applications would have behaved if they have been accepted. Judgemental methods are usually based on only the characteristics of persons who were accepted, and who subsequently defaulted. Credit scoring models take into account the characteristics of good as well as bad payers, whereas, judgemental methods are generally biased towards perceptions of bad payers only.

Scoring models are built on much larger samples than a loan analyst can remember. Scoring models can be seen to include explicitly only legally acceptable variables whereas it is not so easy to ensure that such variables are ignored by loan officer. Credit scoring models demonstrate the correlation between the variables included and repayment behaviour, whereas this correlation cannot be demonstrated in the case of judgemental methods because many of the characteristics which a loan officer may use are not objectively measured. A credit scoring model includes a large number of an applicant's characteristics simultaneously, including their interactions whereas a loan officer's mind cannot do this, the task is too complex. A further important benefit is that given the same data, variables and statistical methodology two statisticians would come to essentially the same weights: they are independent of the person performing the analysis. This is highly unlikely to be so in the case of judgemental methods, (Crook, 1996).

**Criticisms of credit scoring:**
Credit scores use any characteristic of an applicant regardless of whether one can put forward a clear causal relationship to likely repayment. Furthermore, economic factors sometimes are not included. Another criticism sometimes made of scoring models is that an individual may have the characteristics which make her/him more similar to a bad than a good payer, but may have these purely by chance. Statistically the scoring model is incomplete: it omits some variables, which taken with the others, would predict that you will repay. But unless a scoring model has every possible variable in it which predicts for every single person it will misclassify some people. Another criticism which is sometimes made of scoring models is of indirect discrimination, [for more details see, (Crook, 1996)].

Furthermore, these models are not fail-safe. They are only as good as the original specification, and one limitation is that the data are historical. Though the original discriminant analysis may have produced a Z score which was fairly accurate, unless it is frequently updated, either the variables or weights, assumed to be constant over time, make it less accurate. This problem can be minimised if the bank keeps records of its type-I and type-II errors, and acts to implement a new model to address any necessary changes. A more difficult problem is that the model used imposes a binary outcome: either the borrower defaults or does not default. In fact, there is a range of possible outcomes, from a delay in interest payments to non-payment of interest, to outright default on principal and interest. Often the borrower announces a problem with payments, and the loan terms can be renegotiated. These different outcomes can be included, but only two at a time, (Heffernan, 2005).

By looking at how such credit scoring works, an applicant for credit is evaluated in a credit scoring system by simply summing the points received on the various application characteristics to arrive at a total score. This score may be treated in a number of ways depending on the system design. In the single cut-off method, the applicant's total score is compared to a single cut-off point score. If this score exceeds the cut-off, credit is granted; otherwise the applicant is rejected. More complex systems are based one a two-stage process. For example, the applicant's total score may be compared to two cut-off points. If the score exceeds the higher cut-off, credit is awarded automatically, while if it falls below the lower cut-off, credit is automatically denied. If the score is between the two cut-offs, credit history information is obtained, scored, and the points added to the total score obtained from information in the application form (some other approaches re-evaluate the applicant according to their requirements). If this new score is above a new higher cut-off, credit is awarded; if not, credit is denied, (Capon, 1982).

Altman and Haldeman (1995) have **suggested steps to follow for corporate credit scoring models** as follows:

- Applying primary client-data to credit scoring models
- Testing a credit scoring model
    - Definition of risk
    - Model development
    - Test of time
    - Stability
    - Public versus private company data
    - Probability of failure
    - Credibility
    - Model support
    - Pilot testing
- Using a supplemental system:
    - Firm- capital market approach (i.e. using systematic beta risk)
    - Firm-econometric approach.

So, the main thrust of this research is to develop a model (a credit scoring model) to evaluate credit risk in the banking sector in Egypt. The investigative stage of this research is to conduct informal interviews with key personnel in Egyptian banks in order to evaluate credit policies and to establish potential key factors. Results so far revealed that most banks in Egypt use judgemental techniques in their evaluation process.

By reviewing all previous lines of enquiry, in addition to the results of the pilot study that exhibited that all banks in Egypt, with which the researcher made informal interviews do not use such a model to evaluate their credit risks. The researcher is considering developing an integrated model for both consumers and small businesses to evaluate credit risks in the banking sector in Egypt, especially since credit scoring models have undergone a noticeable success in different environments in USA and Europe, taking into account all requirements for the proposed model according to the nature of the Egyptian environment.

The general idea of a credit scoring model rests on identifying some independent variables, which typically reflect the financial position of the client, using a linear equation to estimate the ability of the client to repay. The dependent variable would represent a total score. Depending on this total score, the decision-maker takes the logical decision, as to whether to grant or reject the applicant, (Motawa, 2001).

In addition, the researcher has thought about using some advanced techniques to build the proposed model, for example Excel and VBA (Visual Basic for Application), to enable the creditor to use the model in such a simple way saving effort and time of the credit process,[for more information see: (Sengupta, 2004) and (Jackson and Staunton, 2001)].

**Literature review**

Relevant literature in this research is classified into three groups:
The first group deals with credit scoring models for commercial loans/small business loans.
The second group relates to credit scoring models for consumer loans/personal loans, including credit cards and housing loans.
The third group deals with credit scoring models in general, including a comparison between different techniques used in building credit scoring models.

**The first group:** credit scoring models for small business/commercial loans
By reviewing studies in this group, it is clear that most of these studies used financial ratios in building the credit scoring models [see for more details: (Orgler, 1970); (Falbo, 1991); (Leonard, 1992); (Frame,*et al.*, 2001); (Emel,*et al.*, 2003); (Liang, 2003); and (Cramer, 2004)]. Most of this group handled the scoring models using different types of ratios and almost all the main ratios were repeated in all models with some slight differences.
While the objectives of these studies seem to be different, ostensibly, all of them led to the same result, which is to develop a credit scoring model for small business loans/commercial loans.

However, using the advanced computer programmes in building the scoring systems helped to find out and control all the selected variables in this group, (Tsaih,*et al.*, 2004).
Some of these studies develop credit scoring models to evaluate existing loans [see: (Orgler, 1970); (Kumar and Motwani, 1999); and (Cramer, 2004)] while other studies develop scoring models to see the effect of the total discriminatory function (either discriminant or multi-discriminant) on the quality of the scoring model [see: (Falbo, 1991) and (Liang, 2003)].
One study tried to find the best model in a specific environment in Croatia ,i.e., (Zekic-Susac,*et al.*, 2004), had specific features not found in other environments.
Only one study studied the effect of income-area on the scoring model and then on the small business lending activities, for both low-and moderate-income areas and moderate-and high-income areas census tract, credit scoring is generally associated with increased small business lending activities. Besides, credit scoring is associated with increased “lending out-of-market”, but often with decreased “in-market lending”, (Frame,*et al.*, 2004).

Some of these studies used traditional statistical techniques in building the credit scoring models [see: (Orgler, 1970); (Falbo, 1991);(Leonard, 1992); (Frame,*et al.*, 2001); (Emel,*et al.*, 2003); (Frame,*et al.*, 2004); and (Tsaih,*et al.*, 2004)] except, (Zekic-Susac,*et al.*, 2004), who depended on neural networks, comparing them with more than one conventional statistical technique. The credit scoring model can be considered a tool for allocating the time of bank officers and bank examiners in the review and evaluation of existing commercial loans, (Orgler, 1970), and easily altered to cope with changes in the business environment, (Tsaih,*et al.*, 2004).

Statistical association measures showed that the neural network models are better representations of data than logistic regression and CART, (Zekic-Susac,*et al.*, 2004), while discriminant analysis, in general, has better classification ability but worse prediction ability, whereas logistic regression has a relatively better prediction capability, (Liang, 2003).
Thus, it can be said that information technology reduces information costs and asymmetry between borrowers and lenders, using a simultaneous equation model, (Frame,*et al.*, 2001). Some results suggest that applications of credit scoring techniques to areas of credit other than consumer credit may prove to be quite fruitful, (Leonard, 1992).
Finally, all studies in this group that compare credit scoring models using different statistical techniques find no essential differences between them [see: (Emel,*et al.*, 2003), (Liang, 2003); (Cramer, 2004); and (Zekic-Susac,*et al.*, 2004)].

**The second group:** credit scoring models for consumer/personal loans
By having a look at this group, it was found that some of these studies focused on consumer loans [see: (Orgler, 1971); (Steenackers and Goovaerts, 1989); (Kim and Sohn, 2004); and (Sarlija,*et al.*, 2004)]. Whilst other studies focused on credit scoring models for credit cards [see: (Boyes,*et al.*, 1989); (Greene, 1998); (Banasik,*et al.*, 2001); and (Lee,*et al.*, 2002)]. One study investigated housing loans as a type of consumer loan, (Lee and Chen, 2005). Another study discussed the credit scoring efficiency and the development of a scoring effectiveness-measurement tool using some criteria for the evaluation process on consumer loan, (Leonard, 1995).
Besides these, two studies from the consumer loans focused on existing consumer loans [see: (Orgler, 1971) and (Kim and Sohn, 2004)].
In this group, like the first group, the objectives of these studies seem to be different but all of them gave rise to the same result which is to develop a credit scoring model for either consumer loans or credit cards.

Most of these studies depended on conventional statistical techniques, such as discriminant analysis, regression analysis, Probit analysis and logistic regression in building the scoring models [see: (Orgler, 1971); (Boyes,*et al.*, 1989); (Steenackers and Goovaerts, 1989); (Greene, 1998); (Banasik,*et al.*, 2001); and (Sarlija,*et al.*, 2004)]. By contrast the others depended on modern/advanced statistical techniques, such as neural networks and hybrid models, in building the scoring models [see: (Lee,*et al.*, 2002); (Kim and Sohn, 2004); and (Lee and Chen, 2005)] including two studies which made a comparison between traditional and advanced statistical techniques [see: (Lee,*et al.*, 2002) and (Lee and Chen, 2005)].
Most studies in this group depended on case studies either of a bank [see: (Leonard, 1995); (Banasik,*et al.*, 2001); (Lee,*et al.*, 2002); and (Lee and Chen, 2005)] or financial institution, (Boyes,*et al.*, 1989), or credit company [see: (Steenackers and Goovaerts, 1989) and (Greene, 1998)]. However, just one study depended on two banks, (Orgler, 1971).

Almost all studies used similar variables, with some differences regarding the nature of data or in the number of variables from eight variables in (Sarlija,*et al.*, 2004) to twenty five variables in (Banasik,*et al.*, 2001). Some other studies used grouped variables [see for example: (Greene, 1998) and (Boyes,*et al.*, 1989)].

Most studies in this group used two groups of customer credits either "good" or "bad" [see: (Orgler, 1971); (Boyes,*et al.*, 1989); (Banasik,*et al.*, 2001); (Lee,*et al.*, 2002); and (Kim and Sohn, 2004)]. While two studies used three groups of customer credits, one of them used either "good" or "bad" or "refused" , (Steenackers and Goovaerts, 1989), and another study used either "good" or "poor" or "bad", (Sarlija,*et al.*, 2004).

The credit scoring models are designed for practical use. Hence, it is important to determine if they are economically justified. The cost of operating a credit scoring system, once the model has been developed, is quite small, especially in banks that manage their consumer loan portfolio with a computer. While it is relatively easy to estimate this cost, it is very difficult to predict the benefits resulting from the use of a credit scoring model, (Orgler, 1971).

When the scoring model includes both effectiveness and efficiency, the scoring quality index, which includes some criteria for use in the evaluation process, will provide a direct assessment of performance, (Leonard, 1995).
Furthermore, accounting for the selection nature of the historical data will be important. Acceptance/rejection is based on extremely simple easily explained and justified criteria, (Greene, 1998).

The neural network model has the highest average correct classification rate in comparison with discriminant analysis and logistic regression, although results are very close, approaches. Besides, the designed hybrid model not only has better accuracies, but also has the lowest type II error associated with high misclassification costs, (Lee,*et al.*, 2002). Almost the same results were found by (Lee and Chen, 2005) which is that the hybrid model has the best average correct classification rate in comparison with discriminant analysis, logistic regression, MARS and BPN, but with very small differences. Besides, the hybrid model in this study still has the lowest not only type II error but also type I error in comparison with the other statistical techniques.

**The third group:** credit scoring models in general
By reviewing this group of studies, it was found that this group differs from the other two groups in terms of purpose and nature of studies[5].
Most of these studies focused on comparing different statistical techniques used in credit scoring [see: (Guillen and Artis, 1992); (Desai,*et al.*, 1996); (Hand and Henley, 1997); (Baesens,*et al.*, 2003); (Chen and Huang, 2003); and (Ong,*et al.*, 2005)]. Such comparisons were between prevailing/popular statistical techniques and most recent statistical techniques in some cases [see: (Baesens,*et al.*, 2003) and (Ong,*et al.*, 2005)].
Most studies in this group discussed the scoring models, taking into account the two classes of clients which are "good" and "bad" [see: (Guillen and Artis, 1992);

[5] This group of studies discussed credit scoring in general, taking into account the limitations and restrictions that may be faced in building scoring models and the accuracy of the models with a comparison between different statistical techniques used in building the scoring models regardless of the nature of these techniques, either recent, conventional, or even unpopular techniques.

(Desai,*et al.*, 1996); (Hand and Henley, 1997); (Banasik,*et al.*, 2003); (Chen and Huang, 2003); and (Yang,*et al.*, 2004)].

One study focused on a credit union and the effect of new statistical techniques in such scoring models, (Desai,*et al.*, 1996).
Another study focused on credit scoring performance using the Total Quality Management (TQM) concept, (Leonard, 1996).
Some other studies reviewed different statistical techniques that are used in scoring models [see: (Hand and Henley, 1997) and (McGrath, 2003)].
The genetic algorithm, as one of the most recent techniques used in the scoring models, used twice in this group of studies [see: (Desai,*et al.*, 1996) and (Ong,*et al.*, 2005)].
Some of these studies discussed some unpopular techniques in scoring models, such as, The Rorschach Comprehensive System and The Kolmogrov-Smirnov Curve [see: (McGrath, 2003) and (Yang,*et al.*, 2004)].

The possibility of establishing a two step procedure for prediction has been stressed. In fact, this combines the use of discriminant analysis and modelization and it leads to a good global classification rate keeping the number of bad clients accepted as good well below 10%, (Guillen and Artis, 1992).
In an effort to follow TQM principles to the credit scoring industry, the training and continuous improvement programmes must be goal-oriented, and in order to assist in the establishment of these goals, benchmarking must be introduced. For business in general and the credit scoring industry in particular, the need for training and education is becoming more and more apparent, (Leonard, 1996).

In general, there is no overall best statistical technique method used in building credit scoring models, what is best depends on the details of the problem, the data structure, the characteristics used, the extent to which it is possible to separate the classes by using those characteristics, and the objective of the classification, (Hand and Henley, 1997).
All studies that made a comparison between different techniques found that, first, most recent/advanced statistical techniques are better than the traditional ones; second, there is no apparent difference between different statistical techniques in terms of the percentage of correct classification or hit rate.

And sometimes this depends on the original group that is used to compute the correct classification (depending on bad or good and bad together), (Desai,*et al.*, 1996).
When considering both correct classification percentage and area under the curve performance measures, it can be concluded that the non-linear LS-SVM and NN classifiers yield a very good performance. However, the more simple classification techniques, such as linear discriminant analysis and logistic regression, also have a very good performance, which is in majority of the cases not statistically different from that of the LS-SVM and NN classifiers, (Baesens,*et al.*, 2003).

Unfortunately, there is no evidence concerning the degree to which the practice of psychological assessment is flawed by inaccuracies in test administration and scoring. No standardized observational measures are immune to potential misuse, and there is an ethical obligation to ensure that test administration and scoring are conducted fairly and accurately, (McGrath, 2003).

But, in some cases, there is no better approach than classifying randomly, given that one knows the ratio of good to bad in the whole population, (Yang,*et al.*, 2004).
Finally, genetic programming outperforms other models. Furthermore, artificial neural networks and logistic regression can also provide the satisfied solutions and can be an other alternative. Compared with other popular models, genetic programming is more suitable for credit scoring models. The discriminant function, which is derived by genetic programming, can provide a better forecasting performance than the other algorithms, (Ong,*et al.*, 2005).
Lastly, by reviewing the previous discussion in the three groups, the researcher intends to develop two or three models[6]. One will be for the small business, the second for the personal loans and the last for credit card purposes, at the same time three statistical techniques will be used: discriminant analysis, logistic regression and one of the neural networks models as some of the most popular and successful techniques apparent in the literature, especially in such a new environment that has specific features.

The chosen environment will be the Egyptian banking sector, in which no studies have investigated the use of sophisticated statistical appraisal techniques in credit scoring. Indeed, from the review of literature to date, no studies were found in Egypt, or in the rest of the Middle-East countries, except for one study in Qatar[7],(Al Amari, 2002). Therefore, the researcher intends to cover that gap, which was found in the Egyptian banking sector.

**Methodology**

**The research importance can be summarized as follow:**

- There are no Arabic studies (to the extent of the researcher's knowledge) dealt with statistical techniques in the field of evaluating credit risks using a model such as a credit scoring model.
- This research contributes to clarifying the concepts related to credit risk evaluation.
- This research contributes to determining the requirements of credit scoring in the field of credit risk evaluation.
- This research contributes to developing an integrated theoretical framework to credit risk evaluation for those interested in this important field.
- This research contributes to providing the decision makers in the banking sector with a suitable methodology for making logical credit decisions.

[6] The number of models that will be developed depends on the availability of the data, in other words if the data are available for all the three models, then three models will be developed; otherwise, the researcher will restrict the breadth of the study.
[7] One PhD thesis was found, which focused on the role of credit scoring in credit evaluation in Qatar.

Therefore, the **main concern of this research** is that "**there is no integrated model for evaluating credit risk in banking sector in Egypt despite the rapid increase in funds-size invested as credit granted by these banks**".

**So, the objectives of current research are to:**

- Identify the currently used techniques in evaluating credit risk in Egyptian banks then, evaluate these techniques.
- Develop a proposed model to evaluate credit risk in Egyptian banks.

A credit scoring model is the proposed model to evaluate credit risk taking into account all relevant factors in the Egyptian environment, which clearly appeared from the pilot study.

**The hypothesis of this study:**
The core hypothesis of this research is that: "**$H_0$: there is no significant difference in the effectiveness of alternative credit scoring techniques applied to Egyptian banks**".

**The proposed models:**
The researcher will depend on both traditional/conventional and modern/recent statistical techniques used to build credit scoring models which are:

- Discriminant analysis
- Logistic regression
- Neural networks, as follow:

**Discriminant Analysis:**
Discriminant analysis is a statistical technique which allows the researcher to study the differences between two or more groups of objects which respect to several variables simultaneously, (Klecka, 1980).
The following figure (2) exhibits the relationship between groups and discriminatory variables:

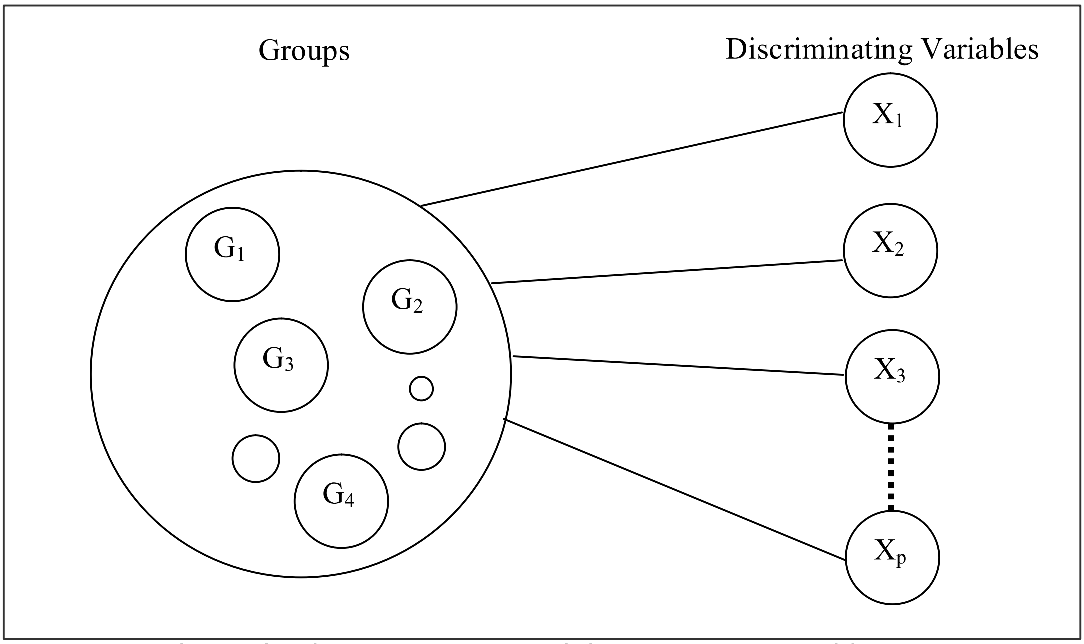


Figure (2): Relationship between groups and discriminatory variables
Source: (Klecka, 1980), p.10.

There are many types of Discriminant Analysis (DA), such as Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA) and Multiple Discriminant Analysis (MDA), the latter of which the researcher intends to use, depending on the nature of data that will be available in the research.

**Logistic Regression:**
Regression methods have become an integral component of any data analysis concerned with describing the relationship between a response variable and one or more explanatory variables.
It is important to understand that the goal of an analysis using logistic regression is the same as that of any model building technique used in statistics.
What distinguishes a logistic regression model from the linear regression model is that the outcome variable in logistic regression is binary or dichotomous.
This difference between logistic and linear regression is reflected both in the choice of a parametric model and in the assumptions. Once this difference is accounted for, the methods employed in an analysis using logistic regression follow the same general principles used in linear regression, (Hosmer and Lemeshow, 1989). If a simple linear regression equation model using weighted least squares violates the constraints on the model or does not properly fit the data, it can be said that it may need to use a curvilinear model. The simple logistic regression model can easily be extended to two or more independent variables. Of course, the more variables, the harder it is to get multiple observations at all levels of all variables. Therefore, most logistic regressions with more than one independent variable are done using the maximum likelihood method, (Freund and William, 1998).
On theoretical grounds it might be supposed that logistic regression is a more appropriate statistical tool than linear regression, given that two discrete classes “good” and “bad” have been defined, (Hand and Henley, 1997).

**Neural Networks:**
The study of Neural Networks (NNs) is an attempt to understand the functionality of the brain. In particular it is of interest to define an alternative "artificial" computational form that attempts to mimic the brain's operation in one or a number of ways. In the last few years interest in the field of NNs has increased considerably, due partly to a number of significant break-throughs in research on network types and operational characteristics, but also because of some distinct advances in the power of computer hardware which is readily available for net implementation.
Neural network elements:
Neural networks, in general, consist of a number of simple node elements, which are connected together to form either a single layer or multiple layers. The relative strengths of the input connections and also of the connections between layers are then decided as the network learns its specific task(s).
The basic node elements employed in NNs differ in terms of the type of network considered. The following figure shows one commonly encountered model. In this, the inputs to the node take the form of data items either from the real world or from other network elements, possibly from the outputs of nodes in a previous layer.

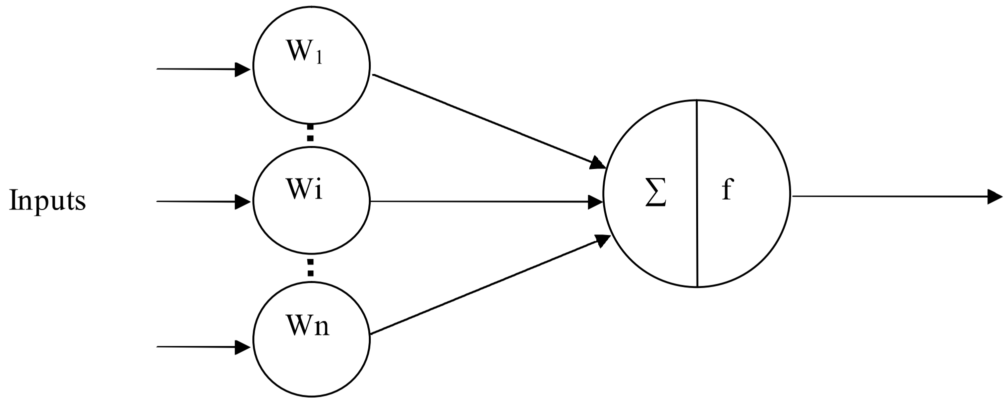


Figure (3): Basic neuron model
Source: (Irwin,*et al.*, 1995), p. 3.
The output of the node element is found as a function of the summed weighted strength inputs.
Neural networks are adaptive nonlinear systems that adjust their parameters automatically in order to minimise a performance criterion. This obviously links them to adaptive and optimal control.

**The proposed variables of this study:**
The researcher figured out all proposed variables from two sources: first, are the literature reviews, second, is the pilot study that the researcher conducted as informal interviews with the key persons in Egyptian banks in order to make out the current used variables which differ from the literature variables in a part of it. The researcher intends to use both types of variables in building the proposed scoring models, either in the proposed consumer credit scoring model or the small business credit scoring model.

Variables classified into three sections as follows:
First, some variables which appropriate to personal loans, including credit cards include: name, age, time at the present address, telephone, owning a credit card, etc.
Second, another group of variables of this type which are appropriate to small business scoring models and the most suitable variables, as the literature has stressed, are financial ratios, such as: gross profit, current ratio, inventory turnover, gross profit margin, cash ratio etc.
Third, all new variables, which were not mentioned in the previous two types and the pilot study, differ from the usual variables used in the literature such as: good personal reputation of the client, guarantee, investigation report, field visit of the client etc. [For more details about all study variables see for example: (Steenackers and Goovaerts, 1989); (Emel,*et al.,* 2003); (Liang, 2003); (Sarlija,*et al.,* 2004); (Zekic-Susac,*et al.,* 2004)].

**Data collection of this study:**
The research sample comprises all banks working in Egypt, which the researcher will focus only on the main head offices (a total of 59 banks). The research will be limited to two samples, first, commercial banks, which are 28 banks, second, business and investment banks, which are 31 banks[8].
Data collection sources:

- Egyptian banks (the historical data, specially related to credit processes);
- Datastream; and
- Bankscope.

and perhaps also a questionnaire, because the proposed models may include some qualitative data.
Data can be described as qualitative or quantitative. Qualitative data are concerned with qualities and non-numerical characteristics, whilst quantitative data are all data that are collected in numerical form. And qualitative data can be classified as discrete or continuous. Discrete data can take only one of a range of distinct values; for example, the number of employees. On the other hand, continuous data can take any value within a given range, such as time or length (Collis and Hussey, 2003)].

**Pilot study:**
The researcher conducted informal interviews with the credit department managers in three banks which are regarded as the top banks in Egypt, in order to evaluate

[8] Egyptian banking system structure: (1) Commercial Banks (28 banks): Public Sector Banks (4 banks) and Private and Joint Venture Banks (24 banks). (2) Business and Investment Banks (31 banks): Private and Joint Venture Banks (11 banks) and Branches for Foreign Banks – Off-Shore Banks - (20 banks). In addition to Specialized Banks (3 banks): The Egyptian Industrial Development Bank, The Arab Egyptian Real Estate Bank and Principal Bank for Development and Agriculture Credit. Egyptian banks abroad are not included, also two banks established under private laws and are not registered with CBE; namely, Arab International Bank, and Nasser Social Bank.
Source: Bank, E. C. 2002. The Egyptian central bank. Economic Journal. **42**

credit policies, and to establish potential key factors[9], during the period between 22/12/03 and 05/02/04, and the interviews took the shape of open questions with the credit department managers.

This pilot study so far revealed that those banks in Egypt[10] used judgemental techniques in the evaluation to the credit process. Furthermore, this process depends almost exclusively on the decision of the evaluator (credit department team, especially the department manager).

## Conclusion

As it mentioned before this research aims to identify the currently used techniques in evaluating credit risk in Egypt's banking sector, then to evaluate these techniques and to develop model(s) to evaluate credit risk in Egyptian banks. In a pilot study, the researcher conducted informal interviews with key personnel in three of the Egyptian banks, in order to evaluate credit risk policies.

Expected results in this research can be classified into two sections as follows:
First, the expected results relate to expected statistical techniques:
The pilot study showed that these banks in Egypt[11] do not use any of the statistical techniques in the evaluation process. So, the researcher expects that there will be differences between the existing techniques and the proposed techniques in terms of the results of the evaluation process, which will be reflected in the prediction ability in the future, after the implementation of the proposed techniques.

Second, the implementation of the research:
At the final stage of the research an investigation will be conducted, by means of a questionnaire survey of Egyptian banks, into attitudinal aspects of implementation of sophisticated techniques. Logistic regression[12] will be run in order to attempt to establish any significant link between the degree of predisposition to implementation and other banks characteristics, for example, size and number of branches.

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[9] The informal interviews took place in the following three banks: Egyptian National Bank, Misr Bank and Misr International Bank (MIBank).
[10] Especially the governmental banks, because the researcher could not accomplish enough meetings with the credit manager in the private banks (just MIBank).
[11] Except one of the three banks seemed to use, in a part of its evaluation, a statistical technique which related to a CRR scoring sheet.
[12] Discriminant analysis and NNs may be run beside the logistic regression.

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