

Consumer Choice Prediction: Artificial Neural Networks versus Logistic Model

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EXTENDED ABSTRACT

Quantitative analysis for forecasting in business and marketing, especially in consumer behaviour and consumer decision-making process (consumer choice modelling), has become more popular in business practices. The ability to understand and to accurately predict the consumer decision can lead to more effectively target the products (and/or services), cost effectiveness in marketing strategies, increasing in sale and result in substantial improvement in the overall profitability of the firm.

Conventional econometric models, such as discriminant analysis and logistic regression have been used to predict consumer choices. However, in recent years, there has been a growing interest in applying artificial neural networks (ANN) to analyse consumer behaviour and to model the consumer decision-making process.

Neural networks are considered as a field of artificial intelligence. The development of the models was inspired by the neural architecture of human brain. Neural networks have been generally applied to two different categories of problems - recognition problems and generalisation problems. Recognition problems include visual applications such as learning to recognize particular words and speak them. Generalization problems include classification and prediction problems.

ANN have been applied in many disciplines, including biology, psychology, statistics, mathematics, medical science, and computer science. Recently ANNs have been applied to a variety of business areas such as accounting, finance, management and decision making, marketing, and production. However, the technique has been sparsely used in modelling consumer choices. For example, Dasgupta et al. (1994) compared the performance of discriminant analysis and logistic regression models against an ANN model with respect to their ability to identify consumer segment based upon their willingness to

take financial risks and to purchase a non-traditional investment product.

The purpose of this paper is to empirically compare the predictive power of the probability neural network (PNN), a special class of neural networks, and the MLFN with the logistic model on consumers' banking choices between electronic banking and non-electronic banking. Data for this analysis was obtained through a mail survey sent to 1,960 household in New Zealand. The questionnaire gathered information on consumers' decision to use electronic banking versus non-electronic banking. The factors include service quality dimensions, perceived risk factors, user input factors, price factors, service product characteristics, and individual factors. In addition, demographic variables including age, gender, marital status, ethnic background, educational qualification, employment, income, and area of residence are considered.

Empirical results showed that both ANN models (MLFN and PNN) exhibit a higher overall percentage correct on consumer choice predictions than the logistic model. Furthermore, the PNN demonstrates to be the best predictive model since it has the highest overall percentage correct and a very low percentage error on both Type I and Type II errors.

1. INTRODUCTION

Quantitative analysis for forecasting in business and marketing, especially in consumer behavior and consumer decision-making process (consumer choice model), has become more popular in business practices. The ability to understand and to accurately predict the consumer decision can lead to more effectively target the products (and/or services), cost effectiveness in marketing strategies, increasing in sale and result in substantial improvement in the overall profitability of the firm. Conventional econometric models, such as discriminant analysis and logistic regression can predict consumers' choices, but recently, there has been a growing interest in using ANN to analyze and model consumer decision-making process.

ANN have been applied in many disciplines, including biology, psychology, statistics, mathematics, medical science, and computer science. Recently, the ANN have been applied to a variety of business areas such as accounting, finance, management and decision making, marketing, and production. However, the technique has been sparsely used in modeling consumer choices. For example, Dasgupta et al. (1994) compared the performance of discriminant analysis and logistic regression models against an ANN model with respect to their ability to identify consumer segment based upon their willingness to take financial risks and to purchase a non-traditional investment product. Fish et al. (1995) examined the likelihood of clustering managers-customers purchasing from a firm via discriminant analysis, logistic regression and ANN models. Vellido et al. (1999), using the Self-Organizing Map (SOM), an unsupervised neural network model, carried out an exploratory segmentation of the on-line shopping market while Hu et al. (1999) showed how neural networks can be used to estimate the posterior probabilities of consumer situational choices on communication channels (verbal vs. non-verbal communications).

2. BANKING CHANNELS AND CONSUMER CHOICE THEORY

The evolution of electronic banking, such as internet banking, has altered the nature of personal-customer banking relationships and has many advantages over traditional banking delivery channels. This includes an increased customer base, cost savings, mass customization and product innovation, marketing and communications, development of non-core businesses and the offering of services regardless of geographic area and time. Furthermore, information technological

developments in the banking industry have speed up communication and transactions for customers. The information technology revolution in the banking industry distribution channels began in the early 1970s, with the introduction of the credit card, the Automatic Teller Machine (ATM) and the ATM networks. This was followed by telephone banking, cable television banking in the 1980s, and the progress of Personal Computer (PC) banking in the late 1980s and in the early 1990s.

Similar to its international counterparts, the adoption of electronic banking such as internet banking is growing in New Zealand. During the last quarter of 2001, there were approximately 480,000 regular internet users utilizing internet banking facilities to conduct their banking transactions. This reflects a 54 percent growth from 170,000 users during the same quarter of 2000 (Taylor, 2002). It is predicted that the usage of internet banking in New Zealand will continue to grow in the near future, as customer support for internet banking is mounting.

Despite its growing popularity, majority of consumer behavior banking studies has focused on a specific type of electronic banking instead of investigating the concept of electronic banking as a whole in relation to consumers' decision making behavior (see Al-Ashban and Burney 2001). Furthermore, the limited electronic banking studies that have been published are descriptive in nature, providing information on basic concepts of electronic banking instead of focusing on complex and in-depth consumer decision making processes (Orr, 1998).

2.1 The Consumer Decision-Making Process

The consumer decision-making process pioneered by Dewey (1910) in examining consumer purchasing behavior toward goods and services involves a five-stage decision process. This includes problem recognition, search, and evaluation of alternatives, choice, and outcome. Dewey's paradigm was adopted and extended by Engel, Kollat and Blackwell (1973) and Block and Roering (1976). Block and Roering (1976) suggested that the environmental factors such as income, cultural, family, social and physical factors are crucial factors that constraint consumers from advancing to the first four stages in the consumer decision-making process.

Analogous to Dewey's (1910) paradigm for goods, Zeithaml and Bitner (2003) suggested the decision-making process could be applied to services. The five stages of the consumer decision-

making process operationalized by Zeithaml and Bitner (2003) were; need recognition, information search, evaluation of alternatives, purchases and consumption, and post-purchase evaluation. Furthermore, they imply that in purchasing services, these five stages do not occur in a linear sequence as they usually do in the purchase of goods.

2.2 Logistic model in electronic banking

For many durable commodities, the individual's choice is discrete and the traditional demand theory has to be modified to analyse such a choice (Ben-Akiva and Lerman, 1985). Let $U_i(y_i, w_i, z_i)$ be the utility function of the consumer i , where y_i is a dichotomous variable indicating whether the individual is an electronic banking user, w_i is the wealth of the consumer and z_i is a vector of the consumer's characteristics. Also, let c be the average cost of using electronic banking, then economic theory posits that the consumer will choose to use electronic banking if

$$U_i(y_i = 1, w_i - c, z_i) \geq U_i(y_i = 0, w_i, z_i) \quad (1)$$

Even though the consumer's decision is straightforward, the analyst does not have sufficient information to determine the individual's choice. Instead, the analyst is able to observe the consumer's characteristics and choice, and using them to estimate the relationship between them. Let x_i be a vector is of the consumer's characteristics and wealth, $x_i = (w_i, z_i)$, then Equation 1 can be formulated as an ex-post model given by:

$$y_i = f(x_i) + \varepsilon_i \quad (2)$$

where ε_i is the random term. If the random term is assumed to have a logistic distribution, then the above represents the standard binary logit model. However, if we assume that the random term is normally distributed, then the model becomes the binary probit model (Maddala, 1993; Ben-Akiva and Lerman, 1985; Greene, 1990). The logit model will be used in this analysis because of convenience as the differences between the two models are slight (Maddala, 1993). The model will be estimated by the maximum likelihood method used in the LIMDEP software.

The decision to use electronic banking is hypothesized to be a function of six variables (measured on a 5-point Likert-type scale) and demographic characteristics. The variables include service quality dimensions, perceived risk factors, user input factors, price factors, service product

characteristics, and individual factors. The demographic variables include age, gender, marital status, ethnic background, educational qualification, employment, income, and area of residence. Implicitly, the empirical model can be written under the general form:

$$EBANKING = f(SQ, PR, UIF, PI, SP, IN, YOUNG, OLD, GEN, MAR, HIGHSCH, EURO, MAORI, RURAL, HIGH, LOW, BLUE, WHITE, CASUAL, \varepsilon) \quad (3)$$

where EBANKING = 1 if the respondent is an electronic banking user and 0 otherwise; SQ (+) = Service quality dimensions; PR (-) = Perceived risk factors; UIF (+) = User input factors; PI (-) = Price factors; SP (+) = Service product characteristics; IN (+) = Individual factors; YOUNG (+) = Age level (1 if respondent age is between 18 to 35 years old and 0 otherwise); OLD (-) = Age level (1 if respondent age is above 56 years old and 0 otherwise); GEN (+) = Gender (1 if respondent is a male and 0 otherwise); MAR (+) = Marital status (1 if respondent is married and 0 otherwise); HIGHSCH (-) = Education level (1 if respondent completed high school and 0 otherwise); EURO (+) = Ethnic group level (1 if respondent ethnic group is New Zealand European and 0 otherwise); MAORI (+) = Ethnic group level (1 if respondent ethnic group is Maori and 0 otherwise); RURAL (+) = Residence level (1 if respondent resides in rural area and 0 otherwise); HIGH (+) = Income level (1 if respondent income level is above \$40,000 and 0 otherwise); LOW (+) = Income level (1 if respondent income level is below \$19,999 and 0 otherwise); BLUE (+) = Employment level (1 if respondent is a blue-collar worker and 0 otherwise); WHITE (+) = Employment level (1 if respondent is a white-collar worker and 0 otherwise); CASUAL (+) = Employment level (1 if respondent is causal worker, i.e. unemployed, students and house persons, and 0 otherwise); ε = Error term.

A priori hypotheses are indicated by (+) or (-) in the above specification. For example, service quality dimensions, user input factors, service product characteristics and individual factors are positively related to the use of electronic banking. Furthermore, consumers' decision to use electronic banking is negatively related to perceived risk factors and price factors.

Demographic characteristics such as age, gender, marital status, education, ethnic group, area of residence, and income were hypothesized to influence the respondent's decision to use electronic banking. Income was divided into low (below \$19,000), medium (between \$20,000-\$39,000) and high (above \$40,000); age group was

divided into young (between 18 to 35 years old), medium (36 to 55 years old) and old (above 56 years old); ethnic group was divided into New Zealand European, Maori, and others (Pacific Islander or Asian); and employment level was divided into blue-collar workers, white-collar worker, casual worker (including unemployed, students and house persons) and retirees. These are dummy variables and one dummy variable is dropped from each group to avoid the dummy trap problem in the model.

3. ANN MODELS

3.1 Multi-layer feed-forward neural network

The ANN model, inspired by the structure of the nerve cells in the brain, can be represented as a massive parallel interconnection of many simple computational units interacting across weighted connections. Each computational unit consists of a set of input connections that receive signals from other computational units, a set of weights for input connection, and a transfer function. The output for the computational unit (node j), U_j , is the result of applying a transfer function F_j to the summation of all signals from each connection (X_i) times the value of the connection weight between node j and connection i (W_{ij}) (see Equation 4).

$$U_j = F_j \left(\sum W_{ij} X_i \right) \quad (4)$$

where F_j is a transfer function which can take many different functional forms.

The multi-layer feed-forward neural network (MLFN) computational units are grouped into 3 main layers – input layer, hidden layer(s), and output layer. If the network has only one hidden layer, and one output (Z) in the output layer, the output of the network can be exhibited algebraically as shown in Equation 5.

$$Z = F \left(\sum_{j=1}^J W_j^{(2)} \cdot F_j \left(\sum_{i=1}^i W_{ij}^{(1)} X_i \right) \right) \quad (5)$$

where Z is the output of the network, F is the transfer function in the output node, $W_{ij}^{(1)}$ and $W_j^{(2)}$ are connection weights from input layer (node i) to hidden layer (node j) and from hidden layer (node j) to output layer, respectively (West et al, 1997).

The calculation of the neural network weights is known as training process. The process starts by randomly initializing connection weights and introduces a set of data inputs and actual outputs to the network. Then the network calculates the

network output and compares it to the actual output and calculated the error. In an attempt to improve the overall predictive accuracy and to minimize the network total mean squared error, the network adjusts the connection weights by propagating the error backward through the network to determine how to best update the interconnection weights between individual neurons.

3.2 Probabilistic neural network (PNN)

The PNN proposed by Specht (1990) is basically a classification network. Its general structure consists of 4 layers - an input layer, a pattern layer, a summation layer, and an output layer. PNN is conceptually based on the Bayesian classifier statistical principle. According to the Bayesian classification theorem, X will be classified into class A, if the inequality in Equation 6 holds:

$$h_A c_A f_A(X) > h_B c_B f_B(X) \quad (6)$$

where X is the input vector to be classified, h_A and h_B are prior probabilities for class A and B, c_A and c_B are costs of misclassification for class A and B, $f_A(X)$ and $f_B(X)$ are probabilities of X given the density function of class A and B, respectively (Albanis and Batchelor, 1999).

To determine the class, the probability density function is estimated by a non-parametric estimation method developed by Parzen (1962) and extended afterwards by Cacoulos (1966). The joint probability density function for a set of p variables can be expressed as:

$$f_A(X) = \frac{1}{(2\pi)^{p/2} \sigma^p n_A} \sum_{j=1}^{n_A} e^{-\frac{(X-Y_{Aj})(X-Y_{Aj})}{2\sigma^2}} \quad (7)$$

where p is the number of variables in the input vector X , n_A is the number of training samples which belongs to class A, Y_{Aj} is the j^{th} training sample in class A and σ is a smoothing parameter.

4. DATA AND METHODOLOGY

Data for this analysis was obtained through a random mail survey sent to 1,960 household in Canterbury Region, New Zealand. The questionnaire gathered information on consumers' decision to use electronic banking versus non-electronic banking. The mail survey was designed and implemented according to the Dillman Total Design Method (1978), which has proven to result in improved response rates and data quality. The response rate of the survey was about 27%. The data set consisted of 527 observations - 384 electronic banking users (EB) and 143 non-

electronic banking users (NEB). LIMDEP software is used to estimate the logistic regression and NeuroShell2 package is used to construct the artificial neural network models.

To examine the predictive power of the models, the out-of-sample forecasting technique is applied. The sample is randomly divided into two sub-samples: a training sample and a forecasting sample. The training sample and the forecast sample contain 422 observations (304 EB and 118 NEB) and 105 observations (80 EB and 25 NEB), respectively. All models are re-estimated by using only the training samples and the out-of-sample forecasting were conducted over the forecasting samples. Then, the classification rates of each model are computed and compared. The model with the highest percentage correct is considered as a superior model.

5. EMPIRICAL RESULTS

The estimated logistic regression Equation 3 is as shown in Table 1. In general, the logit model fitted the data quite well. The chi-square test strongly rejected the hypothesis of no explanatory power and the model correctly predicted 92% of the observations. Furthermore, SQ, PR, UIF, OLD, WHITE, CASUAL, HIGHSCH, HIGH, and RURAL are statistically significant and the signs on the parameter estimates support the a priori hypotheses outlined earlier.

The estimated coefficients indicate that service quality dimensions and user input factors have a positive impact on consumers' likelihood to choose electronic banking. This implies the level of service quality in electronic, the independence and freedom associated with electronic banking and the enjoyment that could be derived from electronic banking will favorably influence consumers' decision in using electronic banking. Perceived risk factors were found as hypothesized, to negatively affect the probability to use electronic banking. Research tells us a consumer who is risk adverse perceives electronic banking as a financial risk when it is not possible to reverse a mistakenly entered transaction or stopping a payment. Furthermore, the threat of personal information accessed by a third party negatively influences a consumer's likelihood to use electronic banking. This supports the finding of Ho and Ng (1994) and Lockett and Littler (1997).

The demographic variables (age, employment, education, income and residence) were also significant in explaining the respondents' probability in using electronic banking. For example, the negative coefficient of the age group

above 56 years showed that senior consumers were less likely to use electronic banking. Senior consumers are more risk adverse and prefer a personal banking relationship to non personal electronic banking. High school respondents may be less likely to use electronic banking due to their low income status. Furthermore, electronic banking transaction could be costly for this age group who primarily work part-time.

Table 1: Consumer Choice Model

Variable ^{1/2/}	Coefficient	S.E.	Marginal Effect	Rank ^{3/}
SQ**	0.9589	0.4295	0.0664	5
PR**	-3.5081	0.4442	-0.2431	1
UIF**	2.2332	0.3336	0.1547	2
PI	0.0595	0.1716	0.0041	19
SP	-0.1069	0.3375	-0.0074	18
IN	-0.2003	0.3100	-0.0139	16
YOUNG	-0.2582	0.6410	-0.0192	14
OLD*	-0.7996	0.5115	-0.0623	7
GEN	-0.1911	0.4109	-0.0134	17
MAR	0.2143	0.4241	0.0152	15
HIGHSCH**	-1.1449	0.3985	-0.0866	4
EURO	0.4724	0.6251	0.0382	11
MAORI	1.1719	1.7379	0.0511	8
RURAL*	0.6655	0.4350	0.0420	10
HIGH*	-0.6430	0.4991	-0.0492	9
LOW	0.3964	0.5173	0.0255	12
BLUE	0.3254	0.5455	0.0209	13
WHITE**	1.4765	0.6114	0.0893	3
CASUAL**	1.4619	0.8873	0.0638	6
Constant	0.1450	2.0079	0.0104	
Log likelihood function	-99.3037	McFadden R ²	0.6777	
Chi squared (df = 19)	417.5549	Prob.	0.0000	
	Predicted	NEB	EB	Overall (n = 527)
% Correct	83.22	95.31	92.03	
% Incorrect	16.78	4.69	9.97	

Note: 1/ Dependent variable is EBANKING.
 2/ * and ** represent 10% and 5% significant level
 3/ Rank is based on the absolute marginal effect.

Additional information can be obtained through analysis of the marginal effects calculated as the partial derivatives of the non-linear probability function, evaluated at each variable's sample mean (Greene, 1990). For example, the consumers' choice of electronic banking is relatively sensitive to the perceived risk (PR) (Rank = 1) and the user input factor (UIF) (Rank = 2), where an unit increases in PR and UIN scores would decrease and increase the probability of being an electronic banking user by 24.31% and 15.47%, respectively.

The overall percentage correct of 92.03 shows that the logistic model is quite accurate in consumers' choice prediction. However, the percentage incorrect indicate that the logistic model is likely to produce Type I error (wrongly reject H₀ or accept non-electronic banking user as electronic banking user) compared to than Type II error (wrongly accept H₀ or accept electronic banking user as non-electronic banking user), as it has 19.78% and 4.69% incorrect on non-electronic

banking and electronic banking classifications, respectively (see Table 1).

Given that the ANN uses nonlinear functions, it is difficult to demonstrate the algebraic relationship between a dependent variable and an independent variable. Furthermore, the learned output or connection weights could not be elucidated and tested. Therefore, only the relative contribution factors and the classification rates are presented in Table 2. Both MLFN and PNN used the same numbers of independent variables as the logistic model for the input layer nodes. The best network for the MLFN in this study is the one hidden layer network with 19 hidden neurons (19-19-1) and applies the logistic function as the activation functions. For PNN, the network requires the number of pattern units must be at least equal the number of training patterns and the number of summation units must equal to the number of classes (or choices). Thus, the network configuration is 19-527-2-1.

Table 2: ANNs' Relative Contribution Factor

Input Variable	MLPN		PNN			
	Relative contribution	Rank	Relative contribution	Rank		
SQ	0.0648	5	0.0524	11		
PR	0.1259	1	0.1113	1		
UIF	0.1165	2	0.1091	2		
PI	0.0331	16	0.0960	4		
SP	0.0808	4	0.0563	9		
IN	0.0811	3	0.0808	6		
YOUNG	0.0316	17	0.0092	16		
OLD	0.0406	10	0.0004	18		
GEN	0.0451	7	0.1082	3		
MAR	0.0246	19	0.0576	8		
HIGHSCH	0.0426	8	0.0227	14		
EURO	0.0386	12	0.0258	12		
MAORI	0.0377	14	0.0803	7		
RURAL	0.0480	6	0.0096	15		
HIGH	0.0425	9	0.0236	13		
LOW	0.0313	18	0.0000	19		
BLUE	0.0380	13	0.0559	10		
WHITE	0.0403	11	0.0070	17		
CASUAL	0.0371	15	0.0938	5		
Predicted	NEB	EB	Overall (n = 527)	NEB	EB	Overall (n = 527)
% Correct	86.71	97.92	94.88	99.30	100.00	99.81
% Incorrect	13.29	2.08	5.12	0.70	0.00	0.19

The classification results in Table 2 show that both MLFN and PNN exhibit a superior ability to learn and memorize the patterns corresponding to consumers' choice on the electronic banking. Both of methods have higher overall percentage correct on consumers' choice predictions than the logistic model. Generally, the MLFN model can predict quite well on the electronic banking group but its performance is relatively poor when predicting the non-electronic banking group. In contrast, the PNN can predict well for both groups. Therefore, the PNN is assumed to be the best prediction

model in this study since it has the highest overall percentage correct (99.81%) and a very low percentage error on Type I error (0.70%) with 0.00% of Type II errors.

The relative contribution factors and the ranks in Tables 1 and 2 showed a consistency result across all the models. That is both perceived risk (PR) and user input factor (UIF) have strong influence on the consumers' decision between electronic banking and non electronic banking in all three models, Rank = 1 and 2 respectively, whereas the other variables have strong influence in some models but they might have less influence in another model or vice versa. Therefore, these two factors must be considered and set as high priority factors as they have strong impact to the consumers' decision in choosing between electronic banking and non electronic banking.

The within-sample forecast always yields an upward bias; the out-of-sample forecast is a more appropriate measure of the future predictive power. Table 3 shows the classification rates on out-of-sample prediction for the logistic, MLFN and PNN models. The classification results show that the ANN models are better precision on the out-of-sample forecast than the logistic model. In addition, the PNN model outperforms the MLFN model. The PNN yields the highest overall percentage correct and the smallest error rate for both in sample forecast and out-of-sample forecast. This implies that the PNN can predict consumers' choices more accurately than the MLFN and the logistic model. It can also be considered as the superior model for the consumers' choice prediction.

Table 3: Out-of-Sample Forecast

Model	NEB	EB	Overall (n = 105)
LOGIT			
% Correct	88.00	92.50	91.43
% Incorrect	12.00	7.50	8.57
MLFN			
% Correct	84.00	95.00	92.38
% Incorrect	16.00	5.00	7.62
PNN			
% Correct	96.00	100.00	99.05
% Incorrect	4.00	0.00	0.95

6. CONCLUSION

The estimated results from the logistic regression indicate that age, occupation, qualification, income, area of residence, service quality, perceived risk and user input factor are the major factors which influence consumers' decision between electronic banking versus non electronic banking. The logistic model can be considered as an accurate prediction model because the overall

correct classification rates are high, above 90.00% for both in-sample and out-of-sample predictions. However, its performance does not outperform the ANN models for both in-sample and out-of-sample forecasts.

The ANN yield better prediction results but there are some drawbacks on using the ANN. Firstly, the ANN lack theoretical background concerning the explanatory capabilities. The connection weights in the networks cannot be interpreted or used to identify the relationships between dependent and independent variables. Secondly, there are no formal techniques for non-linear methods to test the relative relevance of the independent variables and to carry out the variable selection process. Finally, the ANN learning process can be very time consuming.

In summary, in term of prediction accuracy, the results present in this paper indicated that the PNN can be successfully implemented to predict consumers' choices because it outperforms both the MLFN and the logistic model. This indicates the superiority of using the PNN for prediction of consumers' choices. Furthermore, the study exhibits the potential of the neural methodology, especially the PNN, as an analysis tool to for marketing research. Since neither the consumers' choices are always binary nor the neural network is limited to the binary choice classification problem, the research on the predictive power of the neural networks on the multiple level classifications would be an area for further research, particularly on the consumers' choice prediction.

7. REFERENCES

- Al-Ashban, A.A., and M.A. Burney (2001), "Customer adoption of tele-banking technology: the case of Saudi Arabia", *The International Journal of Bank Marketing*, 19(4/5), 191-200.
- Albanis, G.T., and R.A. Batchelor (1999), Using probabilistic neural networks and rule induction techniques to predict long-term bond ratings, in M. Torres (Ed.), *Proceeding of the 5th Annual Conference on Information Systems, Analysis and Synthesis*, Orlando: IIIS.
- Ben-Akiva, M., and S.R. Lerman (1985), *Discrete Choice Analysis: Theory and Application to Travel Demand*, MIT Press, Cambridge, Massachusetts.
- Block, C., and K.J. Roering (1976), *Essentials of Consumer Behavior: Based on Engel, Kollat, and Blackwell's Consumer Behavior*, The Dryden Press.
- Cacoullos, T. (1966), "Estimation of a multivariate density", *Annals of the Institute of Statistical Mathematics (Tokyo)*, 18(2), 179-189.
- Dasgupta, C. G., G. S. Dispensa, and S. Ghose (1994), "Comparing the predictive performance of a neural network model with some traditional market response models", *International Journal of Forecasting*, 10(2), 235-244.
- Dewey, J. (1910), *How We Think. Health*, New York.
- Dillman, D.A. (1978), *Mail and Telephone Surveys: the Total Design Method*, A Wiley-Interscience Publication, John Wiley and Sons.
- Engel, J.F., D.T. Kollat, and R.D. Blackwell (1973), *Consumer Behavior (2nd ed.)*, New York: Holt, Rinehart and Winston, Inc.
- Fish, K.E., J.H. Barnes, and M.W. Aiken (1995), "Artificial neural networks: A new methodology for industrial market segmentation", *Industrial Marketing Management*, 24(5), 431-438.
- Greene, W.H. (1990), *Econometric Analysis*, Macmillan Publishing Company, New York.
- Ho, S.S.M., and V.T.F. Ng (1994), "Customers' risk perceptions of electronic payment systems", *The International Journal of Bank*, 12(8), 26-39.
- Hu, M.Y., M. Shanker, and M.S. Hung (1999), "Estimation of posterior probabilities of consumer situational choices with neural network classifiers", *International Journal of Research in Marketing*, 16(4), 307-317.
- Lockett, A., and D. Littler (1997), "The adoption of direct banking services", *Journal of Marketing Management*, 13, 791-811.
- Maddala, G.S. (1993), *The Econometrics of Panel Data*, Elgar.
- Orr, B. (1998), "Community bank guide to internet banking", *ABA Banking Journal*, 90(6), 47-53.
- Parzen, E. (1962), "On estimation of a probability density function and mode", *Annals of Mathematical Statistics*, 33, 1065-1076.
- Specht, D.F. (1990), "Probabilistic neural networks", *Neural Networks*, 3(1), 109-118.
- Taylor, K. (2002). "Bank Customers Logging On." *The New Zealand Herald*. Available (August 10, 2003) <http://www.nzherald.co.nz/storydisplay.cfm?thesaction=technology&thesubsection=&storyID=1291883>
- Vellido A., P.J.G. Lisboa, and K. Meehan (1999), "Segmentation of the on-line shopping market using neural networks", *Expert Systems with Applications*, 17(4), 303-314.
- West, P.M., P.L. Brockett, and L.L. Golden (1997), "A comparative analysis of neural networks and statistical methods for predicting consumer choice", *Marketing Science*, 16(4), 370-391.
- Zeithaml, V. A., and M.J. Bitner (2003), *Services Marketing: Integrating Customer Focus across the Firm (3rd ed.)*, McGraw-Hill Irwin.