

## **A Systemic Approach to the Database Marketing Process**

James E Pearce, Geoffrey I Webb, Robin N Shaw and Brian Garner, Deakin University

### **Abstract**

The role of database marketing (DBM) has become increasingly important for organisations that have large databases of information on customers with whom they deal directly. At the same time, DBM models used in practice have increased in sophistication. This paper examines a systemic view of DBM and the role of analytical techniques within DBM. It extends existing process models to develop a systemic model that encompasses the increased complexity of DBM in practice. The systemic model provides a framework to integrate data mining, experimental design and prioritisation decisions. This paper goes on to identify opportunities for research in DBM, including DBM process models used in practice, the use of evolutionary operations techniques in DBM, prioritisation decisions, and the factors that surround the uptake of DBM.

### **Introduction**

Database marketing (DBM) is often viewed as a tactical marketing tool rather than a strategic one, and as a capability that is easily developed (Cooke, 1994). In fact, DBM is a sophisticated process that requires a systemic approach that integrates a number of organisational departments. Without a systemic approach to DBM, the marketing capability of an organisation may be underdeveloped.

The term 'database marketing' will be used in this paper to include business-to-consumer applications of direct marketing, where direct contact is made with a customer. DBM is an interactive approach to marketing using individually addressable media and channels (Shaw, 1993). The terms 'data mining' and 'predictive modelling' are used interchangeably to mean the process of analysing customer data to produce models that predict the behaviour of the population in question.

Much of the advanced practice in DBM is performed within private organisations, which may explain partly the lack of articles published in the academic literature that study DBM issues (Blattberg, 1987; Bult and Wansbeek, 1995; DeTienne and Thompson, 1996; Dwyer, 1989).

The successful use of DBM as a strategic tool can give competitive advantage to an organisation. The benefits of DBM include improvements in the ability to control costs, plan budgets and measure marketing plan performance, the identification of strategic advantage through better use of customer and market information, the facilitation of long-term customer relationships that increase lifetime value and loyalty, improved accuracy in customer segmentation, and the ability to relate customer characteristics to behaviour (Desai *et al.*, 2001; Desai *et al.*, 1998; Lewington *et al.*, 1996). However, a major inhibitor to DBM is that it requires strategic and organisational changes beyond technological superiority to gain many of the benefits of its capabilities.

## **The Database Marketing Process**

DBM has its origins with catalogue retailers based in the USA selling directly to customers. The principal channel used was direct mail, and mailing of new catalogues usually took place to the whole database of customers (DeTienne and Thompson, 1996). Analysis of the results of the mailings led to the adoption of techniques to improve targeting, such as CHAID (Chi-Squared Automated Interaction Detection) and logistic regression (DeTienne and Thompson, 1996; Magidson, 1988; Schoenbachler *et al.*, 1997). The addition of centralised call centres and the Internet to the DBM mix introduced the elements of interactivity and personalisation (Kelly, 2000). During the 1990s, the data-mining boom popularised such techniques as artificial neural networks, market basket analysis, Bayesian networks and decision trees (Berson *et al.*, 2000; Coates *et al.*, 1994).

The increasing sophistication of DBM requires extension of the existing process models. Current DBM capabilities are still evolving at different speeds within different industries and geographical locations. Barriers to the adoption of DBM include the cost of development, poor data and system quality, a lack of a DBM strategy and a lack of a company-wide marketing orientation (Desai *et al.*, 1998). A research opportunity exists to examine the uptake of DBM and factors that encourage uptake.

## **Database Marketing Models**

Early DBM models concentrated on a one-off marketing campaign, where there were a number of potential marketing treatments to be offered to different customer segments. This model was extended for a campaign containing new, untested treatments, such as the launch of a new product (Morwitz and Schmittlein, 1997). Different treatments were offered to a sample of the target population in a testing phase before offering the most effective treatments to the remainder of the eligible customer base (Levin and Zahavi, 1996). In Blattberg's model (1987), marketing is continued to responsive customers. A refinement to this model occurs with the addition of a predictive modelling step to refine the targeting of customers rather than using simple metrics of responsiveness and average order value (Berson *et al.*, 2000).

The three-element model proposed in Lewington *et al.* (1996) identifies the database, a market modelling process, and a mechanism for performance measurement feedback as being the important elements for effective DBM. Although it covers the major elements of DBM, this model does not illustrate the complexity of the process required for successful DBM.

Taking a more detailed view of DBM is the 'closed loop' model, in which DBM is seen as part of a process of organisational learning (Hirschowitz, 2001). Hirschowitz's model identifies the key steps as being idea generation, analysis, customer targeting and treatment allocation, campaign creation and response measurement, campaign execution, campaign monitoring and campaign refinement. The monitoring of campaigns feeds information back to the campaign refinement and idea generation stages. Metrics to evaluate the success of the campaign are defined as part of the campaign development process. However, the closed-loop model fails to consider the integration of experimental design and predictive modelling within an environment in which each campaign is a part of an overall marketing strategy.

A recent addition to the existing paradigm, assisted by technological innovation and the advent of the Internet, is for the marketing effort to take place opportunistically: that is, when

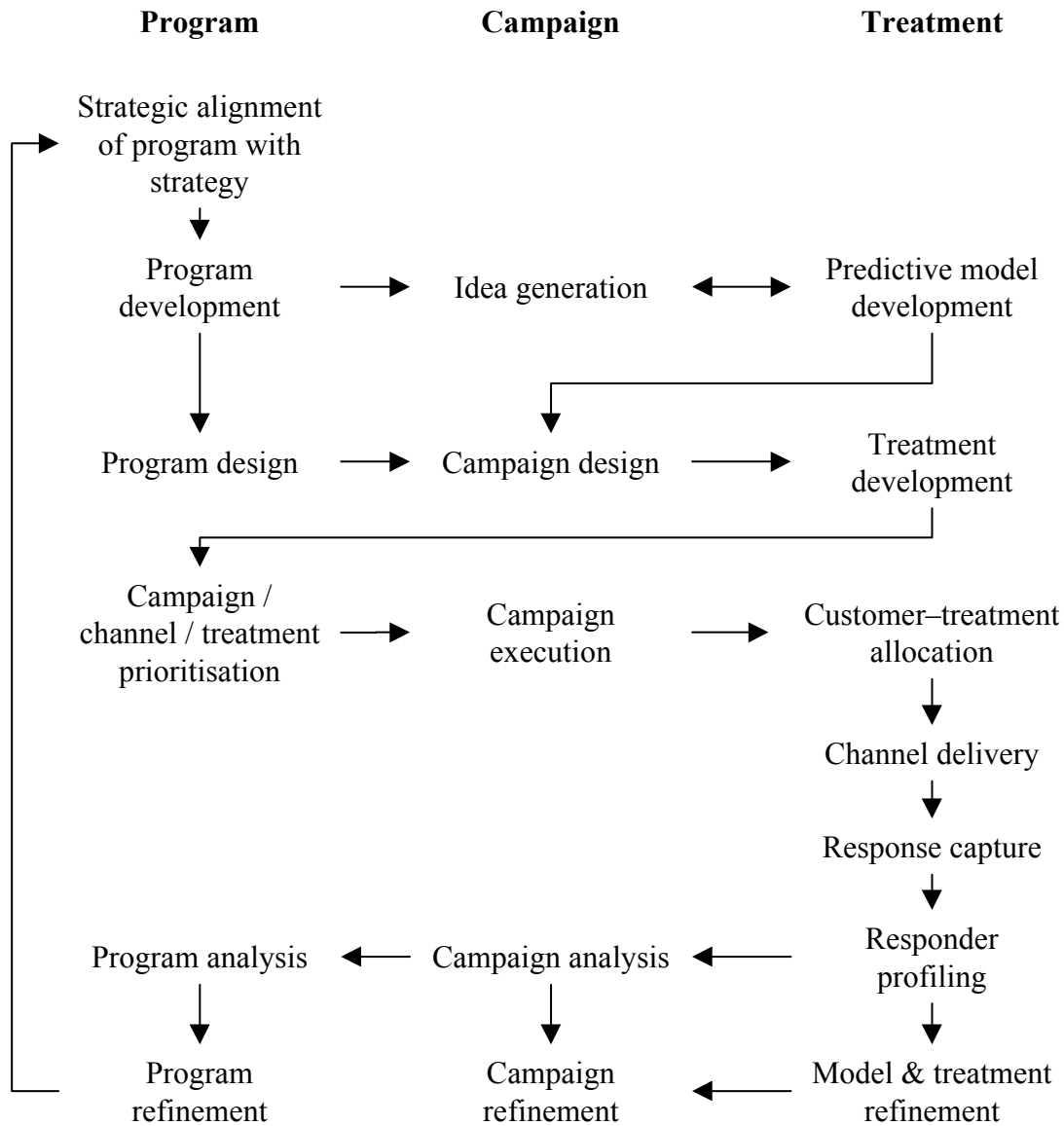
the customer contacts the organisation, a list of campaigns for which the customer is eligible is delivered immediately (Herschel, 2001).

### **A Systemic Model**

In the transformation of DBM from being a mass marketing channel, marketers are making frequent, highly targeted offers over a variety of marketing channels, including direct mail, call centres, email and the world-wide web (Doyle, 2000). Consequently, the amount of DBM activity is increasing within an organisation. We contend that as this marketing activity increases, a number of issues become paramount in importance: once a marketing campaign has been designed and developed, execution of the campaign process must require little or no human intervention (Levin and Zahavi, 1996); technology used must support development and management of a large number of predictive models, but in a way that supports analysts rather than replacing them (Hand, 1998); the process of monitoring of the campaign and predictive model performance must be automated; and there must be a capability to manage many campaigns concurrently in line with business policy, and to plan customer-focused communications. The systemic process proposed in this paper has been formulated to cope with some of these issues, specifically the management and monitoring of predictive models and campaign performance, extending the models found in the literature.

Figure 1 outlines the steps in the systemic process model. Each step takes place at one of the three levels: the program level, the campaign level and the treatment level. The program level is the overarching strategic level at which campaigns and customer communications are coordinated. At the program level there can be a number of campaigns, and a campaign may consist of a number of treatments. At the campaign level, treatments are coordinated to achieve a particular strategic or tactical objective. Predictive model development takes place at the treatment level, identifying those customers most likely to respond to the treatment favourably. Models are refined as responses to treatments are captured and fed back to the marketing database. Experimental design principles are used at the program and campaign design stages to test customers' responses to varying marketing stimuli, and to collect data for the measurement of campaign performance and the refinement of predictive models. The prioritisation stages manage multiple predictive models to ensure that optimised decisions are made in terms of the allocations of customers to communications channels, campaigns and treatments.

Lewington *et al.* (1996) contend that a comprehensive model of DBM is of interest both to the academic community and practitioners. However, the systemic model – introduced in this present paper – more accurately reflects sophisticated DBM practice than the models found in the earlier literature, including Lewington *et al.* (1996). It also provides practitioners with a template from which organisations can build their internal DBM capabilities. Our model's specific areas of innovation are to take an overarching view of DBM that explicitly integrates data mining with experimental design and the need for program-, campaign- and customer-level prioritisation. A more detailed framework for integrating experimental design, predictive modelling and prioritisation decisions for event-triggered and opportunistic campaigns is given in another paper by the current authors. Research remains to be done on the extent to which companies involved in DBM adhere to the process model in Figure 1.



**Figure 1. A Systemic Database Marketing Process Model**

### **Database Marketing and Analytical Techniques**

One of the most attractive aspects of DBM to an organisation is its ability to test the marketing approaches (Shaw, 1993). One of the deficiencies in the literature noted by the authors of this paper is the lack of integration of data mining and experimental design in DBM. By changing the levels of key factors to be tested, causal information can be added to the database. Causal inferences can then be drawn with some confidence of the likely effects, and treatments can be designed to optimise those effects. Thus, the aims of the design process are to capture information about the effects of different treatments on different customer segments so that causal inferences may be drawn, and design must be closely linked to analysis and predictive modelling. Almquist and Wyner (2001) provide a good overview of the use of experimental design for targeted marketing, extolling the benefits of multi-variable testing and illustrating the points nicely with case studies, extending the work of other authors (Berger and Magliozzi, 1993; Paas, 2002; Vriens *et al.*, 1998). However, the use of designed

marketing experiments to provide evidence of causation in a data-mining framework is rarely seen.

Another application of experimental design theory overlooked in a marketing context is that of response surface optimisation (as used in Box and Draper, 1998). Some of these concepts are used in Rossi (1996) to determine the optimal coupon to send a household. Generalisation of such techniques to a DBM application remains an area for future research, for example, the identification of optimal product configurations.

One question of interest to sophisticated DBM practitioners has been that of to which customer to make an offer. This has been generally approached as a single-dimensional question, with a predetermined offer being made to an optimised segment of customers (Bhattacharyya, 1998; Gönül and Meng, 1998; Levin and Zahavi, 1998; Ling and Li, 1998). Current DBM practice demands that these decisions be extended to be multi-dimensional, incorporating multiple channels and campaigns concurrently (Berson *et al.*, 2000; McDoniel and Monteleone, 2002). A research opportunity exists to develop and evaluate algorithms that make such decisions.

### **Conclusion**

The processes that surround the implementation of data mining into the operations of a marketing department can be complex. Some parts of the process can be automated, and some are best left for human judgement (Levin and Zahavi, 1996). An integral part of the overall success or otherwise of DBM is the fusion between the emerging technology and the human factor concerning innovation, assessments and judgements.

Successful strategic assessment of the components of DBM requires that a systemic view be taken, that the program planning stage includes definition of metrics, that programs and campaigns are designed to evaluate the metrics along with model performance, treatment effectiveness and the impact on customer value, and that responses are captured. The ability to manipulate causal variables and assess the effects over a period of time gives marketers the tools required to optimise the return on marketing programs.

The systemic approach represents an opportunity for organisations to improve their current DBM. Increased efficiency will be realised by the proper alignment of an organisation's skills with the task at hand. The ability of the organisation to learn and to apply the learning to future activity will mean increased marketing effectiveness. We have identified a number of areas of opportunity for future research, including research on the process models used in practice, the use of evolutionary operations techniques in DBM, prioritisation decisions, and the factors that surround the uptake of sophisticated DBM.

## References

- Almquist, E., and Wyner, G., 2001. Boost Your Marketing ROI with Experimental Design. *Harvard Business Review*. 79(9), 135–141.
- Berger, P. D., and Magliozzi, T. L., 1993. Experimental Design in Direct Mail and the Application of Taguchi Methods. *Journal of Direct Marketing*. 7(3), 44–54.
- Berson, A., Smith, S., and Thearling, K., 2000. *Building Data Mining Applications for CRM*, New York: McGraw-Hill.
- Bhattacharyya, S., 1998. Direct Marketing Response Models using Genetic Algorithms. In Agrawal, R., and Stolorz, P. (Eds.). *The Fourth International Conference on Knowledge Discovery and Data Mining*. New York: American Association for Artificial Intelligence, 144–148.
- Blattberg, R. C., 1987. Research Opportunities in Direct Marketing. *Journal of Direct Marketing*. 1(1), 7–14.
- Box, G. E. P., and Draper, N., 1998. *Evolutionary Operation: A Statistical Method for Process Improvement*, New York: Wiley.
- Bult, J. R., and Wansbeek, T., 1995. Optimal Selection for Direct Mail. *Marketing Science*. 14(4), 378–394.
- Coates, D., Doherty, N., and French, A., 1994. The New Multivariate Jungle: Computer Intensive Methods in Database Marketing. *Journal of Marketing Management*. 10, 207–220.
- Cooke, S., 1994. Database Marketing: Strategy or Tactical Tool? *Marketing Intelligence & Planning*. 12(4), 4–7.
- Desai, C., Fletcher, K., and Wright, G., 2001. Drivers in the Adoption and Sophistication of Database Marketing in the Services Sector. *The Service Industries Journal*. 21(4), 17–32.
- Desai, C., Wright, G., and Fletcher, K., 1998. Barriers to Successful Implementation of Database Marketing: A Cross-Industry Study. *International Journal of Information Management*. 18(4), 265–276.
- DeTienne, K. N., and Thompson, J. A., 1996. Database Marketing and Organizational Learning Theory: Toward a Research Agenda. *Journal of Consumer Marketing*. 13(5), 12–34.
- Doyle, S., 2000. Software Review: The Components of a Marketing Automation Solution in a Multi-Channel Real-Time Environment. *Journal of Database Marketing*. 8(1), 87–92.
- Dwyer, F. R., 1989. Customer Lifetime Valuation to Support Marketing Decision Making. *Journal of Direct Marketing*. 3(4), 8–15.
- Gönül, F., and Meng, Z. S., 1998. Optimal Mailing of Catalogs: A New Methodology Using Estimable Structural Dynamic Programming Models. *Management Science*. 44(9), 1249–1262.

- Hand, D. J., 1998. Data Mining: Statistics and More? *The American Statistician*. 52(2), 112–118.
- Herschel, G., 2001. *Optimizing Customer Relationship Management through Every Interaction*. Stamford: Gartner.
- Hirschowitz, A., 2001. Closing the CRM Loop. *Journal of Targeting, Measurement and Analysis for Marketing*. 10(2), 168–178.
- Kelly, S., 2000. Analytical CRM: The Fusion of Data and Intelligence. *Interactive Marketing*. 1(3), 262–267.
- Levin, N., and Zahavi, J., 1998. Continuous Predictive Modeling: A Comparative Analysis. *Journal of Interactive Marketing*. 12(2), 5–22.
- Levin, N., and Zahavi, J., 1996. Segmentation Analysis with Managerial Judgment. *Journal of Direct Marketing*. 10(3), 28–47.
- Lewington, J., de Chernatony, L., and Brown, A., 1996. Harnessing the Power of Database Marketing. *Journal of Marketing Management*. 12, 329–346.
- Ling, C. X., and Li, C., 1998. Data Mining for Direct Marketing: Problems and Solutions. In Agrawal, R., and Stolorz, P. (Eds.). *The Fourth International Conference on Knowledge Discovery and Data Mining*. New York: American Association for Artificial Intelligence, 73–79.
- Magidson, J., 1988. Improved Statistical Techniques for Response Modeling: Progression Beyond Regression. *Journal of Direct Marketing*. 2(4), 6–18.
- McDoniel, P. B., and Monteleone, J. P., 2002. Simulation and Optimisation in Direct Marketing Part 2: Developing Optimisation Models to Boost Results. *Journal of Database Marketing*. 9(2), 113–118.
- Morwitz, V. G., and Schmittlein, D. C., 1997. *Testing New Direct Marketing Offerings: The Interplay of Management Judgment and Statistical Models*. Cambridge, Massachusetts: Marketing Science Institute.
- Paas, L., 2002. Test Designs for Evaluating the Effectiveness of Mail Packs. *Journal of Database Marketing*. 9(2), 163–169.
- Rossi, P. E., McCulloch, R. E., and Allenby, G. M., 1996. The Value of Purchase History Data in Target Marketing. *Marketing Science*. 15(4), 321–340.
- Schoenbachler, D. D., Gordon, G. L., Foley, D., and Spellman, L., 1997. Understanding Consumer Database Marketing. *Journal of Consumer Marketing*. 14(1), 5–19.
- Shaw, R., 1993. Making Database Marketing Work. *Journal of Information Technology*. 8, 110–117.

Vriens, M., van der Scheer, H. R., Hoekstra, J. C., and Bult, J. R., 1998. Conjoint Experiments for Direct Mail Response Optimization. *European Journal of Marketing*. 32(3/4), 323–339.