

## **Marrying Market Research and Customer Relationship Marketing**

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## **Abstract**

This paper builds on previous research to demonstrate the power of marrying together market research data and existing loyalty card data in improving promotional marketing. In particular, it includes the analysis of real attitudinal data (cognitive, affective and conative) collected specifically for this task from 3,000 customers. The approach is illustrated via a case study of a gardening retailer. It concludes that 5 key factors need to be considered: the relevancy of the product or service on offer, identification with the brand providing the service or product, perceived value for money, the accessibility of the brand or product, and the degree of confidence customers will be satisfied with what they buy. The first two factors are of primary importance, highlighting that you are who you are (attitude), not what you are (demographics).

## Using Market Research in Customer Targeting: an Updated Approach

In 1898 the British Navy found that for every 1000 rounds fired by its battleships only 2% ever hit the target. So Admiral Percy Scott studied the techniques employed by his gunners and discovered that the most accurate were those who were better at allowing for the pitch and roll of the ship. Using this knowledge, he designed an automated aiming mechanism that took their hit rate to over 50%.

Direct marketing is facing a similar dilemma. The information age has reduced the cost of delivering messages and increased exponentially the means of delivering them. The resulting deluge of communication has seen consumers donning their hard hats and rushing for cover. With eleven million tonnes of paper being dropped on UK consumers every year, it is little wonder so many are opting-out. DM emails, internet pop-ups, mobile texts and telephone calls are increasingly being ignored by an increasingly marketing-savvy consumer.

### Taking the Consumer's View

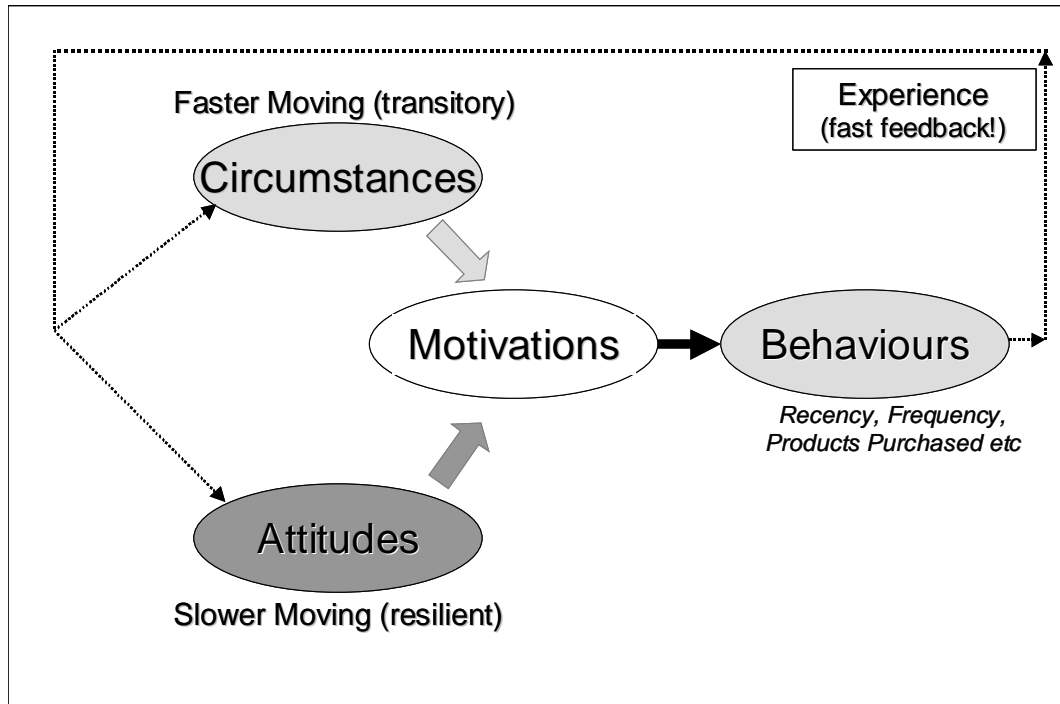
Using insights from market research is an obvious solution to discovering individual customer needs, pinpoint when, where, and how to contact them, and determine the best message to get the job done, yet current attitudes within the DM industry might appear to be against this.

Acland (2004) quotes the MD of one major DM company: *"Market research is useful but it's only the mental picture stuff. If I'm managing the customer, and the revenue that customer represents. I can do that without knowing the 'why?'".* Acland (2004) concludes that market research has a valuable role in influencing the tone of the copy, influencing product development and measuring customer satisfaction but little else, quoting another senior DM executive as saying *"There's a limit to the amount of data you can collect and the number of people you can collect it from. So there's a degree of assumption and therefore inaccuracy in applying the model."*

On the other hand, Leventhal (1997) has shown the value of fusing market research with database marketing. Market research helps to show you where to dig, what tools to use, and how rich a deposit might lie beneath the surface. Furthermore, as Colombo and Jiang (1999) point out, an underlying behavioural model gives greater insight than a pure transaction-based model, enhancing future as well as current decision-making. This is further emphasised by Reinartz & Kumar (2002) who claim that companies need a clearer understanding of the link between loyalty and profits.

### Using Market Research to Understand Customer Motivations

Dick & Basu (1994) propose that behaviours are driven by attitudinal antecedents (cognitive, affective and conative), which are then moderated by social norms and situational influences. Huddleston et al (2004) build on this work to show that an individual's motivations for using a particular retail store are based on a mixture of these attitudinal antecedents, situational influences and social norms. Our research builds further on this approach. The overall approach can be summarised as the Customizer Model shown in Figure 1.



**Figure 1: Customizer Motivational Model**

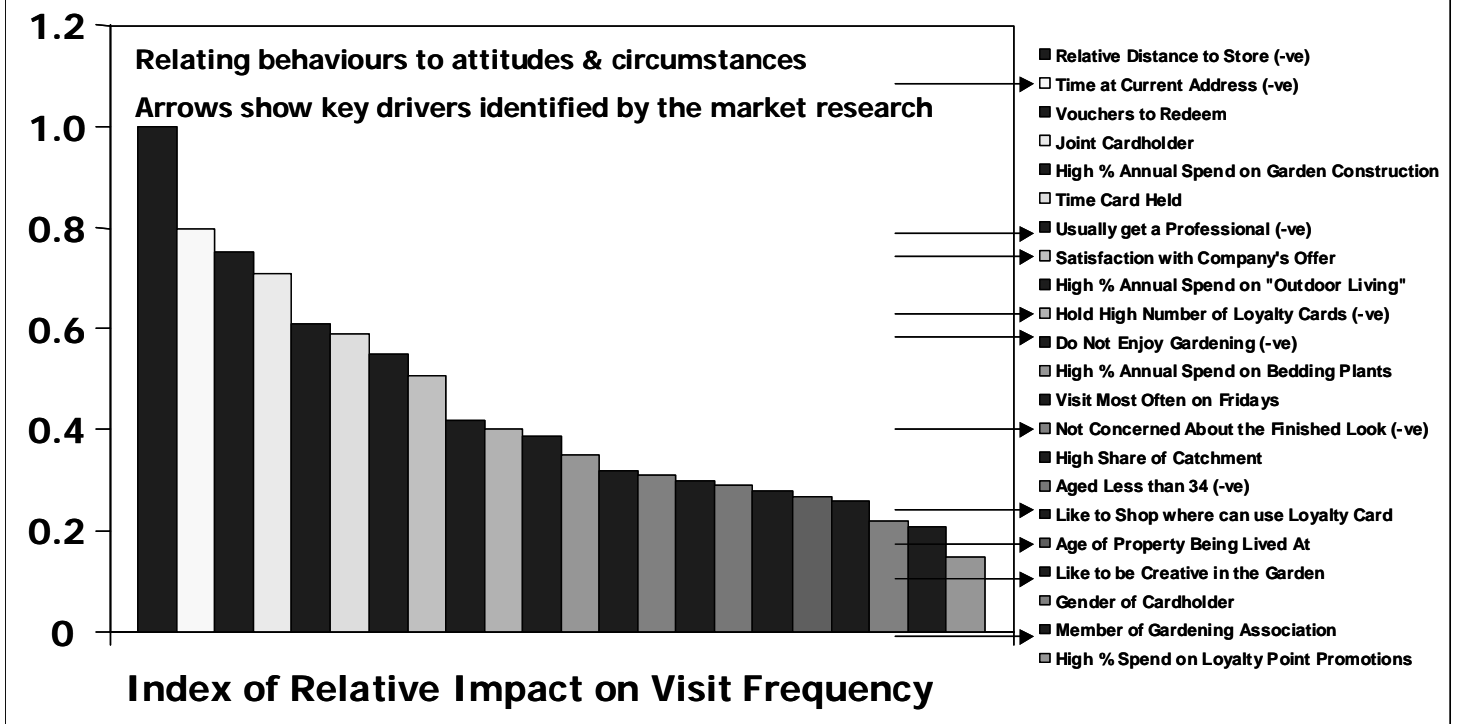
Statistical techniques are employed to compare the attitudes (cognitive, affective and conative), circumstances (situational factors and social norms) and purchases (recency, frequency and value) of a large sample (3,000) of customers, and so develop predictive models of segmented customer behaviour. Given each customer's circumstances, the aim is to identify which attitudes most closely correspond to particular purchasing behaviours, and so better predict customers' likely responses to new and existing propositions. It is worth noting that all of this work is carried out with the explicit consent of the respondent, and in complete anonymity ensuring that no individual is identifiable from the data under analysis.

This approach is very similar to Leventhal's (1997) fusion approach, but with two major differences. Firstly, Leventhal only really considers circumstantial and purchasing data. Our approach also includes a large element of attitudinal data. Secondly, Leventhal focuses on identifying the degree of customer engagement with the category, while our approach focuses much more on understanding the customers' motivations for that engagement.

This approach can be illustrated by presenting case study material for a European gardening retailer where, with the respondents' express permission, we have combined the findings of a dedicated usage and attitude survey with loyalty card transaction data for a sample of over 3000 cardholders. Data analysis was carried out to identify the most statistically significant attitudinal and circumstantial factors that appear to be driving customer purchasing decisions.

For our gardening retailer this enabled motivational models explaining various aspects of garden shopping to be developed. The actual results are confidential but Figure 2 shows the type of model to explain one such factor, visit frequency. As can be seen, the key drivers can be identified enabling the retailer to produce more tailored propositions. For example, a marketing campaign offering vouchers to redeem instore appears to be as motivating for a keen gardener as it is for someone who just wants to clear the weeds from their front garden as long as they live close to the store.

## Drivers of Visits to a Gardening Store



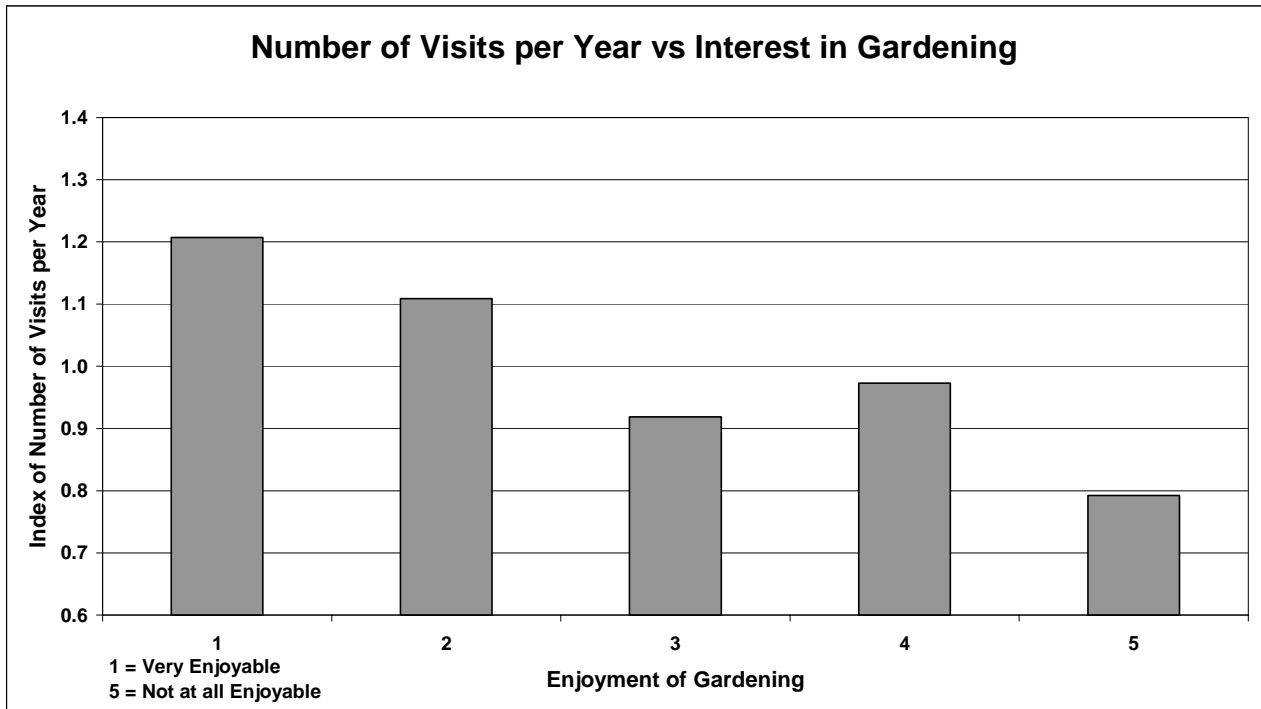
**Figure 2: Drivers of Visits to a Gardening Store**

For each of Dick & Basu's (1994) factors (cognitive, affective and conative antecedents, social norms, and situational influences) the results of this analysis suggest that key motivational drivers can be identified.

### Cognitive factors

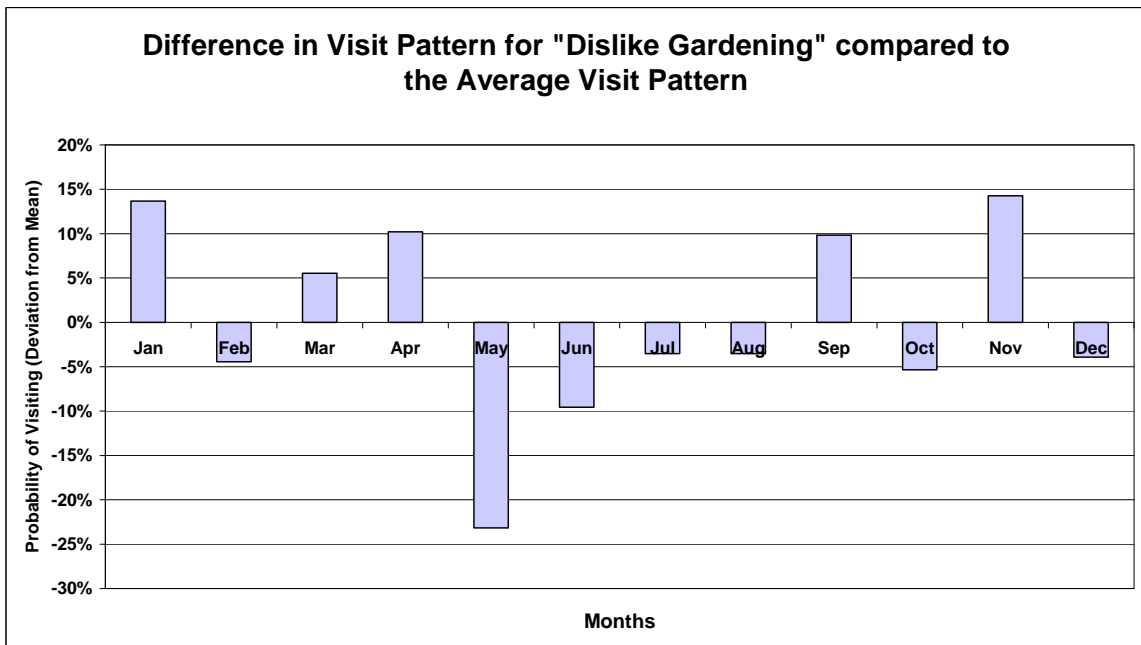
The survey data shows a strong and statistically significant relationship between the number of visits made to the gardening store and the customer's claimed level of interest in gardening (see Figure 3 below).

This is significant because it illustrates how market research uncovers attitudinal drivers that help predict category participation. It also enables us to find spend and visit behaviours that distinguish differing levels of interest, for example, those who enjoying gardening as a hobby, those who only wish to keep the garden neat, and those out to impress.



**Figure 3 Number of Visits per Year by Interest in Gardening**

Figure 4 shows that customers who are more interested in gardening have a different visit pattern compared to others whose total visits and “recency, frequency and monetary” values are similar.

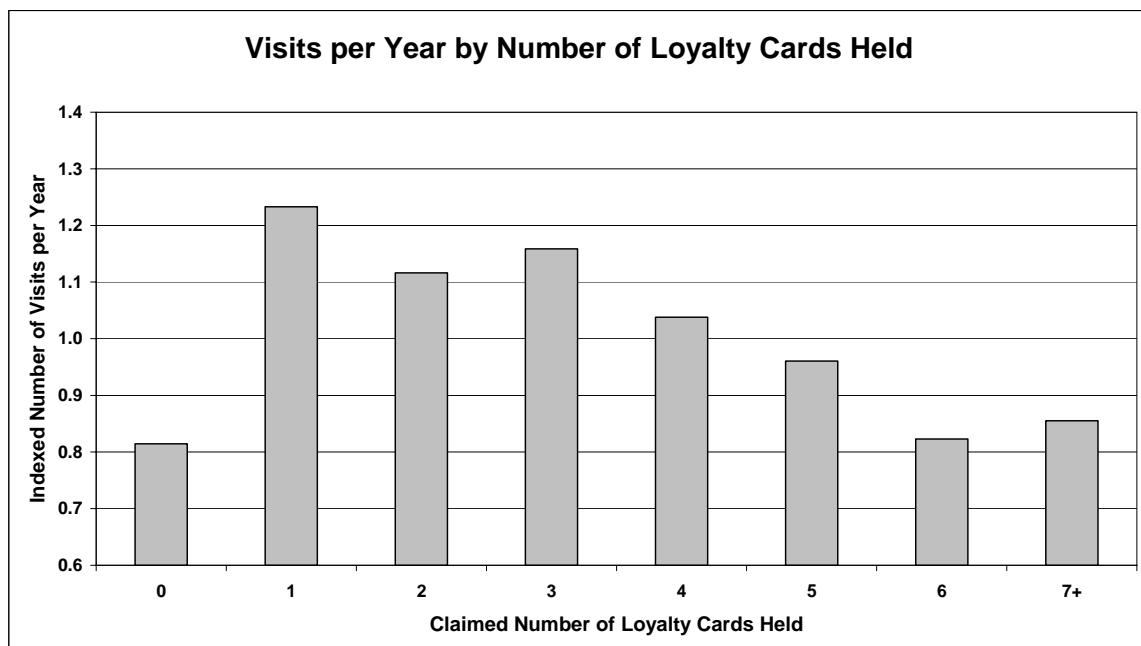


**Figure 4: Seasonal Visit Pattern Differences for Customers who “Dislike” Gardening**

### Affective factors

Many companies have conducted market research studies and have a market segmentation model that separates people according to their likelihood to consider using their brand. Couple this with information from the database and we can now derive how much they are likely to use our brand in specific circumstances.

Figure 5 presents an indirect example of this. It shows that there is a correlation (other things being equal) between number of store visits and number of loyalty cards held.



**Figure 5: Numbers of Visits per Year by Number of Loyalty Cards Held**

Not surprisingly, those holding many cards are less loyal but, more intriguingly, those who claimed not to hold any loyalty cards also visited less. To take part in the survey customers had to be cardholders! This lack of “top-of-mind” awareness of the card suggests a lower brand-engagement, which appears to be reflected in behaviour.

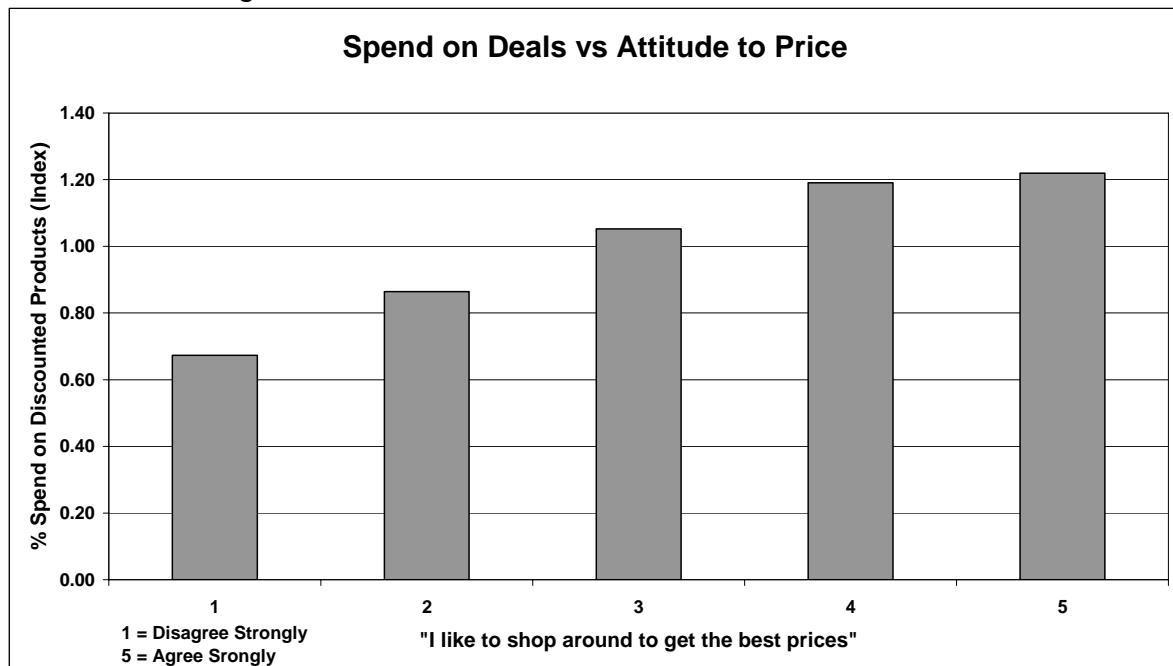
Differences between more- and less-committed users enable us to tailor the message accordingly and better predict likelihood to respond. Combining research and database information provides greater understanding that can be leveraged in marketing communications.

### **Conative factors**

Value for Money reflects the consumer’s ability to change purchase depending on whether the perceived benefit outweighs the perceived cost. For example, any lawnmower will cut the lawn but choosing which one to buy will also depend on the size of your lawn and how much you like mowing. To understand which measures are most predictive of the consumer’s view of Value for Money, we typically consider 3 aspects: the individual’s attitudes to value; the relative price compared to competitor solutions; and the consumer’s view of the total benefit the solution provides relative to competing alternatives.

Market research is especially valuable in uncovering which behavioural characteristics best reflect consumer opinions. If I would not consider buying a Mercedes because of the lack of servicing facilities nearby (a perceived cost), I may become more likely to buy if offered a “free collect and return service”. This may be worth more to me than it costs the dealer to provide. Knowing the relative importance of differing value drivers in the eyes of each consumer will then gives us valuable clues as to their likelihood to respond to an offer.

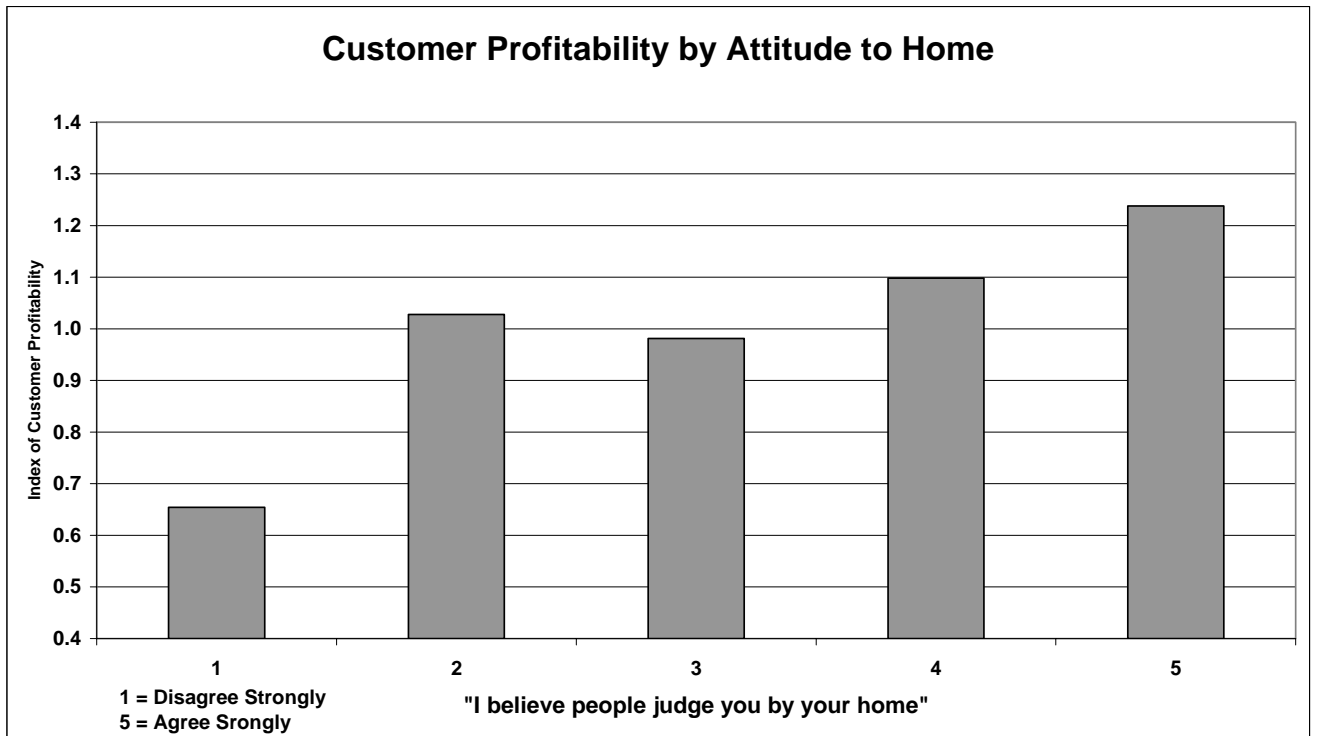
Figures 6 and 7 present examples of how perceptions of Value for Money and attitudes to change influence behaviour.



**Figure 6: Percentage of Annual Spend that is Spent on Discounted Items**

Figure 6 shows a clear relationship between the percentage of the respondent's total actual spend on discounted products and their claimed level of price consciousness. This allows us to compare many other behavioural variables against this dimension in order to understand which are most relevant.

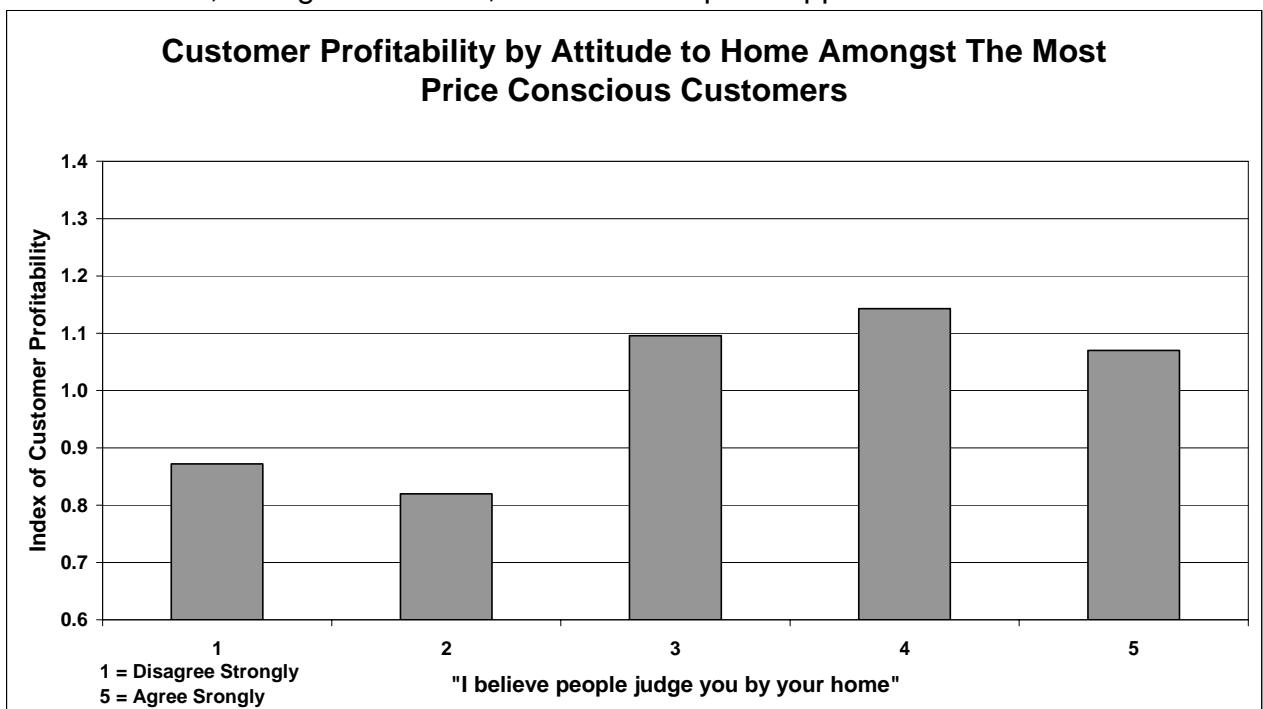
It could be claimed that the behavioural data alone is all that is needed to do this and that the market research information is merely confirming what we already know. Humby (2003), for example, claims that Tesco/dunnhumby use their Clubcard data to identify products that were signatures of people who shop exclusively on price. Accordingly it was identified that buyers of Tesco Value margarine were such consumers and targeting them with price offers was extremely successful. However, this may also be an indicator of disposable income rather than perceived value for money. Someone might never buy Tesco Value Margarine but might readily switch store if they knew the cost of their average basket was going to be 10% cheaper at a supermarket nearby. Being price sensitive does not necessarily mean someone shops exclusively on price.



**Figure 7: Customer Profitability versus Attitude to Home**

Figure 7 shows that attitudes to life change perceptions of Value for Money separately from price sensitivity / price consciousness.

This relationship might be expected to break down for the most price sensitive consumers but, as Figure 8 shows, the relationship still applies.



**Figure 8: Customer Profitability and Attitude to Home for Price Conscious Customers**

Just because someone is more price sensitive than average does not mean other considerations are ignored when judging Value for Money. This demonstrates the type of interconnections that may arise between different types of attitudinal data.

## Situational factors

In retailing, the single most major situational factor is usually distance to store. Figure 9 clearly shows the impact of this situational factor for our gardening retailer.

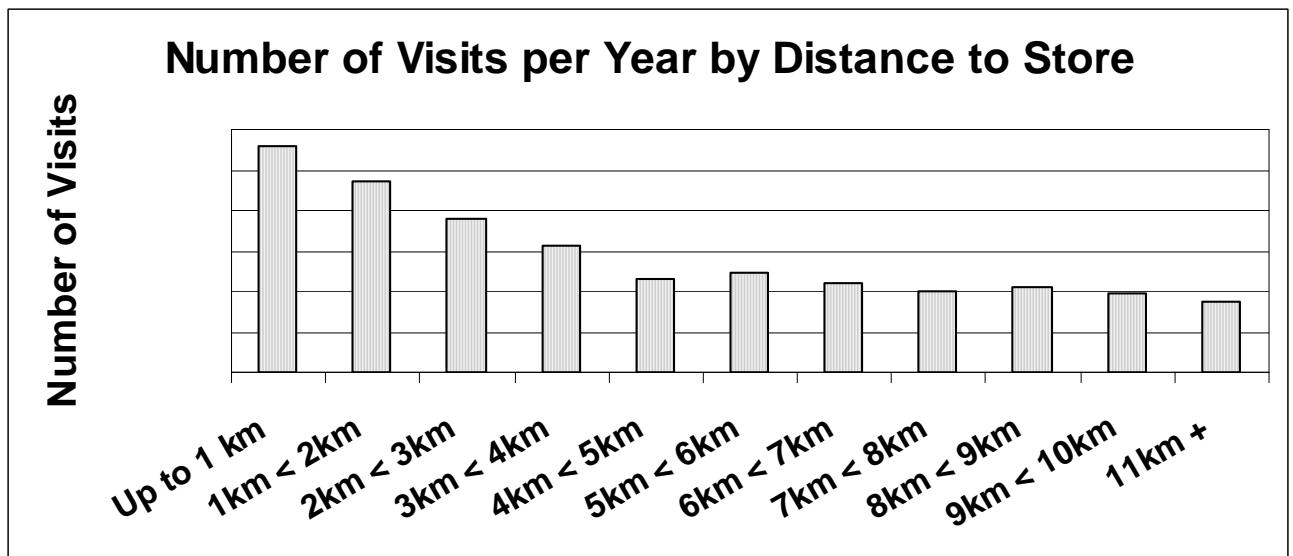


Figure 9: Impact of Distance to Store on Number of Visits per Year

## Social Norms

There are social norms of expected satisfaction that derive from previous experiences of friends and neighbours, comments in the press and so on. For existing customers, current satisfaction is a good indicator, other things being equal, that they are willing to continue to deal with your company. One concept appropriate to CRM is Keiningham & Vavras' (2001) Customer Delight Principle. This asserts that customers' satisfaction levels influence customers' loyalty only when more extreme levels of satisfaction are reached ("Dissatisfaction" or "Delight"). And small changes in satisfaction between these extremes have much less impact. In our view, this is because only these extreme circumstances cause customers to fundamentally reappraise. Dissatisfied customers dismiss future communications either because they doubt the company's competence or feel the company does not care enough about its customers to deserve their business. Delighted customers consider the company is "good" because, even if things go wrong, they care enough to fix the problem. Of course, delighting customers usually costs money. Modelling combined market research and transactional data helps evaluate these trade-offs.

Figure 10 illustrates these effects for two samples of customers using Customer Satisfaction as a measure of consumer confidence.



**Figure 10: Relationship between Confidence in the Brand and Customer Behaviour**

In the first sample, 2258 respondents, we compare the overall level of satisfaction with numbers of visits to the store in the twelve-month period prior to completing the satisfaction questionnaire. In the second sample, 2862 respondents, we compare with number of visits to the store in the twelve-month period after completing the questionnaire.

For the first sample, apart from the highly dissatisfied customers, there is little correlation between visit frequency in the year prior to completing the survey and satisfaction at the end of it. For the second sample, there is a statistically strong and significant correlation between their subsequent visit behaviour and their satisfaction at the start of it. Moreover, the largest differences in behaviour for this group occur for the Dissatisfied and Delighted customers for whom the index value compared to their neighbouring groups show the widest variation (7% - 10%). Amongst the “Merely Satisfied” groups the differences in behaviour are much smaller.

Interestingly, the visit frequency for the Highly Dissatisfied group who completed the questionnaire at the start of the year was not as low as for those who did not. It is therefore possible that by having had the opportunity to “Have their say” some of their negative attitudes were calmed and the potential negative impact on their behaviour moderated. This is supported by previous research, such as Carr (1999).

Similar results exist for their levels of spend, average spend per visit and likelihood to respond to CRM communications. So customer satisfaction should be a key element in our targeting models even though we may not be able to survey the satisfaction of everyone on the database. We must instead find measures of customer behaviour that indicate whether they are likely to be “Delighted”; “Dissatisfied”; or “Merely Satisfied”.

## **Applying the Results to CRM**

The proposed approach has several key advantages. It is possible to see and understand the key drivers and define the measures one needs. This approach evaluates the CRM proposition from the consumer's perspective and intrinsically identifies the drivers of acceptance of a proposition not just its potential applicability. Crucially, it is more predictive of actual consumer response than simple attitudinal segment flags, as shown in the benefits section below. Transactional data is retrospective. Incorporating market research puts the customer's opinions at the heart of your targeting. New and existing propositions; known and potential requirements; prospective and existing customers can all be explored in a consistent and marketing-oriented way, and valuable insights uncovered that would otherwise be missed.

Whether your customer data is derived from on-line or off-line transactions, or even if it only contains quite basic information about your customers, the same approach can be applied. This paper has highlighted one example, but the approach has been applied in other settings, for example in mobile phone retailing. Bringing together the behavioural and circumstantial data from an existing database with the attitudinal and circumstantial data derived from market research produces customer insights that should enhance the returns from a CRM programme. Armed with this knowledge, communications can be tailored to individual customer groups based on their potential receptiveness to your proposition and couched in terms they find most motivating. The proposition can be refined to fit individual customer needs more closely.

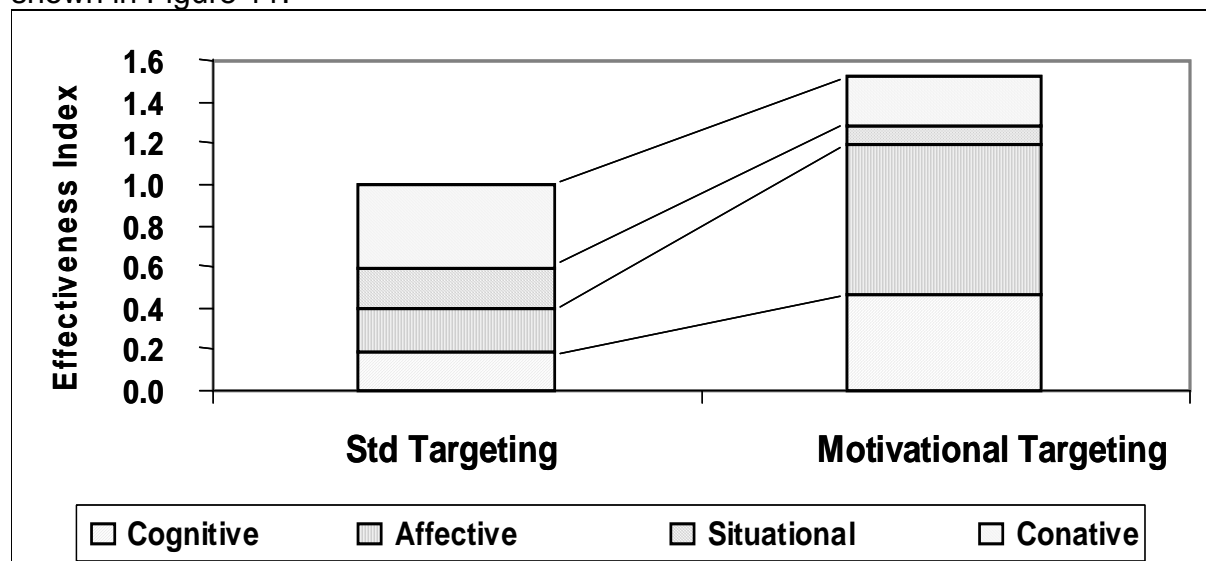
Other initiatives, such as gathering potential leads from contact databases, web-site referrals and so on, can be analysed and profiled using the same techniques. Their potential can be better judged and, perhaps more importantly, the investment needed to exploit them can be more easily justified. Another example, with a direct sales force and a call centre operation, used the model to better predict what type of proposition would be most motivating and whether a prospect was likely to convert. This helped prioritise staff time on the best opportunities and increased conversion rates by 38%.

In addition, understanding which measures of customer behaviour are most predictive of differing customer attitudes enables us to project attitudinal data with confidence across the database without having to survey to every customer. Typically we find some highly predictive attitudinal or circumstantial information, usually between 3 and 6 key items, which cannot be proxied using data already on the database. In this case, mechanisms are required to obtain this information on a more continuous basis. Furthermore, we also know whether this is needed for all customers or only certain groups, so market research surveys can also be targeted and so made more cost-effective.

## **Case Study Benefits**

For reasons of confidentiality, it is not possible to highlight the absolute commercial value of the above case study. However, it is possible to say that the immediate benefits achieved by the gardening retailer were a step-change in promotional response rates of more than 50%, which generated additional profits and an overall project ROI in excess of 500.

With the exception of Social Norms that are group-based by definition, it is also possible to show how the factors described contributed to this improvement, as shown in Figure 11.



**Figure 11: Response from the Customizer Model versus Client's Original RFM Model**

To make the communications more relevant and target customers who were more likely to respond, the model placed greater emphasis on cognitive factors, such as product/service relevancy, and on targeting people with greater propensity to the affective factors, primarily brand commitment. This supports the notion that you are who you are, as represented by attitudes, rather than what you are, as represented by demographics. These customers are generally less price sensitive and tend to have more potential to uplift spend. More value-driven messages were directed at price-sensitive customers who were most likely to both switch and then repeat purchase. The result was more sales-effective and more profitable marketing campaigns, increasing ROI's from 2:1 to 10:1.

### **Conclusion: The Marriage of Market Research and Database Marketing**

In modelling customer-specific data from loyalty card schemes, we identified that the ability to satisfy consumer needs can be more effectively met by understanding the 5 dimensions based on Dick & Basu's (1994) model:

- Cognitive: The **Relevancy** of the Product or Service on Offer
- Affective: **Identification** with the Brand providing the service or product
- Conative: Perceived **Value for Money**
- Situational: The **Accessibility** of the Brand or Product
- Social Norms: The **Confidence** customers will be satisfied with what they buy

Using market research in developing one-to-one targeting models is both feasible and, if done correctly, highly productive. It requires considering the five key drivers of response and using the data to model the relationships between attitudes, behaviours and circumstances. In so doing it provides a new approach to targeting effectiveness.

It helps to tell you how to mine your data; what to look for; what extra data to collect and what themes and messages would be most beneficial in driving response rates. Identifying and validating such opportunities is where mixing market research and transactional data comes into its own. This means that we can understand the impact of customer attitudes without surveying the entire database and without needing to develop a projective model for attitudinal segment membership that is reliant on poorly predictive geo-demographic data. The market research delivers the information we need to relate each individual's attitudes and circumstances to their recorded purchase behaviour.

We can find the measures we need to create to identify customers with differing motivations, and what else is needed to reliably predict their engagement with the category and brand. Moreover, we can quantify how much better these models will be compared to existing models.

We can use the model for "What if..?" modelling to evaluate the relevancy, appeal and hence "*size of the prize*" of potential new propositions.

This brings increased predictability and more easily justifiable database marketing investment.

The ability to analyse cross-matched survey and customer data enables us to understand both the "What?" and "Why?" of consumer behaviour and the learnings directly impact on database marketing strategies. Such analyses will only increase in the future as more and more digital communications are used for customer contact and tracking. The benefit of taking this more considered approach will be a step-change in targeting accuracy, and an improvement in effectiveness that we hope would make even Admiral Scott proud.

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