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Loyalty program planning and analytics

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Abstract

Purpose – The paper aims to review and critique the current state of loyalty program planning and analytics, highlighting a number of process and methodological deficiencies.

Design/methodology/approach – A general loyalty program planning approach is outlined, designed to build a foundation for a profitable loyalty initiative.

Findings – The paper demonstrates the importance of robust customer insights to program planning and its ongoing management; it also challenges the accuracy of the conventional buyer loyalty measurement approach. In particular, the paper highlights the flaws of the dichotomous loyalty classification which makes often unreasonable category purchase requirements assumptions.

Originality/value – The alternative to the loyal customers vs brand switchers buyer categorization is offered, which allows customers to be single-brand loyal, multi-brand loyal or brand switchers. An explicit brand buyer loyalty categorization is presented, built around explicit differentiation between repurchase exclusivity and brand loyalty.

Keywords Loyalty schemes, Process planning

Paper type General review

An executive summary for managers and executive readers can be found at the end of this article.

Buyer loyalty initiatives

The proliferation of consumer databases is rapidly redefining marketing practices across industries. The influx of consumer, market and competitive insights is transforming marketing art into science, increasing its productivity through better targeting. As a result, the "one size fits all" mass marketing is slowly giving way to data-driven, segmented and differentiated promotions.

Exemplifying the new face of marketing are brand loyalty programs, a broad category of reward-based initiatives aimed at stemming customer attrition. Already common in the frequent usage product categories such as retail, travel or hospitality, buyer loyalty programs are slowly spreading into other consumer product and service categories, including auto and entertainment. Taking advantage of rapidly advancing informational technologies, these marketing initiatives are emerging as the most effective means of finding and retaining brands' most profitable buyers.

In spite of their promise and growing popularity, many buyer loyalty programs become financial liabilities instead of self-funding business assets. Often struggling to convert initial consumer interest in the program itself into incremental product purchases, they deliver poor return on their investment. The loyalty initiatives' economic underperformance typically stems from a lack of broader strategic program rationalization, manifesting itself in technology and incentive overspending. In other words, infrastructure and incentive spending decisions are often made without the support of thorough cost-benefit analyses.

Sources of underperformance

Dearth of sound loyalty program investment rationalization is usually a function of two, highly interrelated factors: inadequate program planning and insufficient customer insights. The former signals a lack of well-defined, robust planning frameworks, while the latter points to inadequate data-analytical supports. Absent these two key supports, loyalty program contact cadence and treatment[1] strategy decisions end being based on intuition than objective data. In addition, program participant recruitment tends to take the form of customer self-selection supported by open-to-all, mass communicated offers.

Treatment strategy and participant recruitment inefficiencies are typically overlooked until the effects of adverse customer selection[2] are felt, which usually manifest themselves through a frequently noted correlation between program registrants' price sensitivity and their propensity to register. In other words, the initial rush of program registrants is usually followed by disproportionately small increases in brand consumption. In the end, even the most technologically advanced and creatively ingenious programs end up subsidizing current customers, while only marginally contributing to sales incrementality.

Also worth mentioning is the quality of the available information, best exemplified by the choice of program performance metrics. One of the most commonly used assessment tools is the registration rate, which is a simple tally of the number of customers signing up with the program. Somewhat less evident is that this metric equates program performance with non-purchase behaviors, which can easily lead to erroneous conclusions. Although indicative of the initial program's appeal, the non-purchase requiring customer registration is neither the end objective of loyalty initiatives, nor is it predictive of future sales gains. It is, however, easily

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obtainable and interpretationally simple which explains the metric's widespread popularity.

Poor choice of metrics is sometimes a result of limited data, but more often it is a product of undisciplined analytics. Inexperienced analysts, time pressures and the overwhelming quantities of data combined with the lack of clear database analytical standards often takes away from the validity of analytical efforts. Further compounding those challenges is the self-focus of individual data domains. Transactions captured through POS, consumer opinions collected with surveys or marketing program results gathered online or by mail are usually housed in separate, differently structured[3] datasets, further divided by departmental boundaries, skill sets and narrow objectives. Considerable informational synergies are lost because of the failure to convert domain-specific data into customer attributes, where a full view of buyer interactions links marketing actions with purchase outcomes.

The purpose of this article is to suggest a series of loyalty program planning and analytics related improvements to circumvent the current process limitations. The ideas presented here are rooted in hands-on loyalty program planning and measurement experience and are primarily focused on methodological improvements. The ultimate objective of these improvements is to turn good buyer loyalty ideas into valuable business assets.

Building a profitable loyalty program

It is often said that success is 95 percent perspiration and 5 percent inspiration. In some sense that is true of buyer loyalty initiatives, where a kernel of a unique idea and a great deal of disciplined planning and analysis are needed for a successful program to emerge. To make the most of the "perspiration" aspect of building a robust initiative, these efforts should be focused on a few critical aspects.

First and foremost, clearly state your program's end objective – is it a net increase in the brand's revenue or profitability? If it is the former, focus on product-level price elasticity considerations, which means a broad-based program built around volume discounts and cash rebates. On the other hand, if the growth in net profitability is your objective, focus on buyer-level repurchase propensity, which translates into careful customer target selection and tailored offerings deemphasizing price discounting. Keep in mind that a loyalty program can boost your brand's revenue if it is built around price incentives, or it can be a profit generating tool if it is focused on identifying and attracting highest value customers. Avoid the temptation to pursue both of these goals simultaneously or you run the risk of missing both targets.

Second, select appropriate impact measurement metrics. The frequently used customer registration rate is a poor indicator of program performance because it relates the impact of the program to an activity that – by itself – delivers little-to-no economic value to the brand. Do not forget that the role of a loyalty initiative is to drive repurchase – program registration is merely a mean to that end. To avoid overstating the impact of your treatment strategy, express its performance in terms of program-attributable sales gains, or comparable revenue producing activities (e.g. re-enrollment, renewal, etc).

Finally, make your program's target audience strategy explicit and operationally clear. Most programs are built around open consumer self-selection, meaning that anyone can elect to participate. The alternative is to invite only a select group of customers. Due to the adverse customer selection, the "open" approach usually attracts scores of registrants but generates not nearly as many incremental purchases. On the other hand, the invitation-based approach focusing only on pre-qualified customers may generate fewer registrants but typically yields higher purchase incrementality. Buyer self-selection based recruitment is attractive because it is easy to execute, but the added complexity of differentiated treatment typically more than pays for itself in greater sales gains. It is important to note, however, that the effectiveness of the invitation-based audience strategy depends on the availability of robust customer pre-qualification[4] insights.

Figure 1 presents a high level view of a program planning process of building economically sound customer loyalty initiatives.

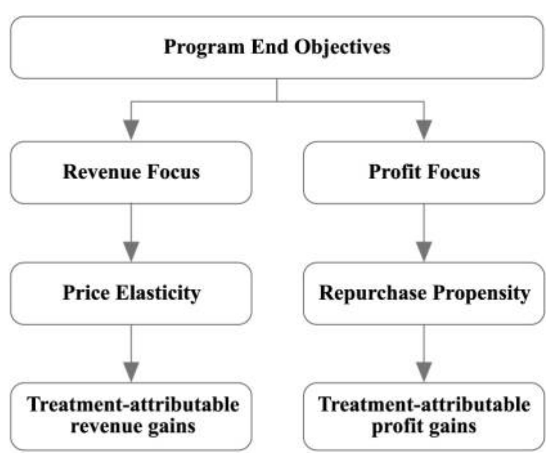
Loyalty analytics

The best plans are those built around objective facts and fact-supported projections. Yet few loyalty initiatives have the right information available at the right time. The first step toward changing that is to identify and prioritize the most critical analytical tasks. To that end, most programs' economic success is dependent on answering the following three (albeit loaded) questions:

(1) *Who are the best customers and what is their value to the franchise?* Analytic competency needed: customer-level value assessment and classification.
(2) *How much should be spent to retain those customers and what are the best incentives?* Analytic competency needed: treatment-level incentive type and dollar amounts.
(3) *How are specific campaigns and incentives performing against their stated goals?* Analytic competency needed: program impact measurement.

The first of the three sets of insights forms the basis for scaling and rationalizing the level of program investment. Building on its findings, incentive and offer identification (number 2 above) pinpoints the most effective contact and offer strategy to drive loyalty programs' economic success. Finally, program impact measurement (number 3) supports reliable and objective assessment of sales or revenue incrementality.

Figure 1 A high level view of loyalty analytical planning



Jointly, these capabilities form a loyalty program support continuum that helps to steer it toward long-term profitability. As shown in Figure 2, they are sequentially dependent, which means that findings from number 1 are used as inputs into number 2 and outcomes of number 1 and number 2 are incorporated into number 3.

Methodologically, these are self-contained analytical competencies requiring unique statistical approaches. For that reason each will be discussed separately, starting with Customer Assessment and valuation, followed by Incentive type and level identification and Robust program impact measurement.

Customer assessment and valuation

At its most rudimentary level, customer base assessment is primarily concerned with accurate brand buyer categorization and a meaningful segment description. With an eye toward total customer value, which is a function of a sum of purchases accumulated over a period of time, the overall buyer base is usually divided into brand loyal and brand switching customer groups. The basis for this categorization is typically a single brand repurchase, expressed as a proportion of the brand purchases *vis-à-vis* total product category purchases over a period of time, or:

$$\text{Brand loyalty} = \left(\frac{b}{c}\right)_{t=i}$$

where:

b = number of purchases of the brand of interest;

c = total number of purchases in the overall product category[5]; and

t = the period of time over which the purchases are evaluated, such as 12 or 24 months.

Implicit in this quantification is the equivalence of brand loyalty and repurchase exclusivity. In other words, a truly loyal customer is someone who repurchases only a single brand in the category, as being 100 percent loyal requires that the number of brand-specific purchases be equal to the number of category-wide ones. Allowing for an occasional "straying", brands typically classify as loyal a customer whose share of the brand-to-category purchases meets or exceeds a chosen threshold, such as 70 percent. In more general terms, the frequently used loyalty categorization heuristic classifies brand buyers into loyalty groupings in accordance with the following logic:

- if $(b/c)_{t=i} \geq$ chosen threshold (e.g. 70 percent), the customer is classified as "loyal"; alternatively
- if $(b/c)_{t=i} <$ chosen threshold (e.g. 70 percent), the customer is classified as "switcher".

Although this or a similar decision rule has been used across a wide array of buyer loyalty programs, its appropriateness is limited to situations where consumers are not expected to purchase more than a single brand in the product category within a period of time. In other words, all products in the category offer functionally substitutable bundles of benefits, and consumer choices reflect their brand preferences, not different functional needs.

There are numerous situations where consumers can be expected to purchase more than a single brand in the category for reasons other than brand preference. For example, a consumer with multiple pets may need more than a single brand of pet food for nutritional or related reasons. Using the above brand loyalty categorization heuristic, that consumer's single brand loyalty could not reach the 100 percent upper limit. At the same time, a single pet-owning consumer would not face the same loyalty classification limit. In other words, the brand loyalty categorization heuristic is biased. The key to its enhancement can be found in the closer analysis of implicit brand loyalty – repurchase exclusivity equivalence, and household-level purchase aggregation:

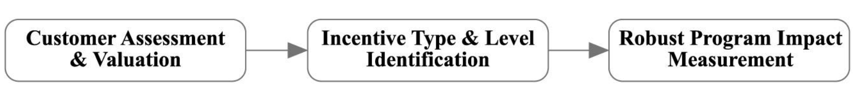
- *Loyalty – exclusivity equivalence*. In a transactional sense, the brand loyalty ratio stipulates that to be considered loyal a brand buyer is expected to repurchase the same brand either exclusively, or least the majority of times when shopping the brand's category. In other words, it is measuring the degree of buyers' repurchase exclusivity. It also means that the line of demarcation between a loyal customer and a brand switcher is highly arbitrary for anyone other than the exclusive brand repurchasers (i.e. 100 percent loyal).
- *Household purchase aggregation*. Also implicit in the current buyer loyalty categorization approach is that brand repurchase analyses are conducted at the transaction level, where the unit of analysis is an "individual buyer-single purchase" conjoint. However, that is rarely the case. In the majority of cases the unit of analysis is a household, which is "individuals living singly or together with others in a residential unit" (Assael, 1995). The reasons for transaction data householding are involved and will not be detailed here, but they include analytically necessary data cleansing and summarizing as well as third-party appending[6]. Specific reasons notwithstanding, given that roughly three-quarters of all households comprise multiple individuals, the sum of category purchases used as the basis for the loyalty ratio is very likely to represent a pooling of multiple individuals' purchases.

Looking back to the loyalty ratio, it is clear that it is in need of re-thinking. Data householding is an analytical reality and it should be reflected in the ratio's computational logic. Household-level purchase data pooling alone warrants decoupling of the brand repurchase exclusivity and brand loyalty, a conclusion that is further reinforced by definitional clarity. Brand loyalty is defined as cross-time product repurchase independent of incentives. Repurchase exclusivity is a special case of brand loyalty, where only a single brand in the product category is being repurchased. All exclusive repurchasers are brand loyal but not all loyal customers are exclusive brand repurchasers.

Enhancing the accuracy of buyer loyalty classification

Before jumping into technical details, let's take a moment to reflect on the origins of the commonly used applied business

Figure 2 High level view of the loyalty analytics development process



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methods or metrics, such as the loyalty ratio and the classificatory heuristic. It seems that more often than not these methods come to be through accidental practices. In other words, pragmatic solutions that "make sense" are copied across organizations and industries, over time gaining acceptance to the point of unquestioned adherence, often in spite of a lack of methodological due diligence.

Yet some of these makeshift heuristics quickly outstretch their usability limits, to the point of becoming misleading. Whether it is due to not being able to keep up with the growing specificity of insights or heightened accuracy expectations, the once-acceptable techniques can become obsolete. That is the case with the brand loyalty categorization heuristic.

As previously noted, the brand loyalty ratio needs to be updated to reflect the rolling up of individual-level purchases to household-level aggregates, as shown below:

$$\text{Household brand loyalty} = \sum\nolimits_{i=m}^{n} h\left(\frac{b}{c}\right)_{t=i}$$

where:
b = number of purchases of the brand of interest;
c = total number of purchases in the overall product category;
t = the period of time over which the purchases are evaluated; and
h = household purchase pooling.

The second, more involved step is to expand the brand loyalty operationalization to accommodate the cross-household variability in category purchase requirements (CPR), thus effectively relaxing the repurchase exclusivity assumption. The new metric capturing these effects – CPR – is defined as an estimated number of distinct product types or brands repurchased by a single household in a product category over a period of time. It enhances the heuristic's classificatory validity by differentiating between single and multi-brand loyalty, effectively replacing the current "loyal vs switcher" dichotomy with a three-category classification of "single brand loyal", "multi-brand loyal" and "switcher". Computationally, the buyer loyalty categorization heuristic should be amended as follows.

If:

$$(k=1)_t \Rightarrow \sum\nolimits_{i=m}^{n} h\left(\frac{b}{c}\right)_{t=i} \geq \text{threshold} = \text{single} - \text{brand}$$

$$\text{loyal, else if}$$

$$(k>1)_t \Rightarrow \left[\sum\nolimits_{i=m}^{n} h\left(\frac{b}{c}\right)_{t=i} / k\right] \geq \text{threshold}$$

$$= \text{multi} - \text{brand loyal, else if}$$

$$(k=1)_t \Rightarrow \sum\nolimits_{i=m}^{n} h\left(\frac{b}{c}\right)_{t=i} \quad \text{or}$$

$$(k>1)_t \Rightarrow \left[\sum\nolimits_{i=m}^{n} h\left(\frac{b}{c}\right)_{t=i} / k\right] < \text{threshold} = \text{switcher}$$

where:
k = household-level CPR estimate;
b = number of purchases of the brand of interest;
c = total number of purchases in the overall product category;
t = the period of time over which the purchases are evaluated; and
h = household-level purchase aggregation.

It should be pointed out that the classificatory validity of above categorization rule is contingent on a sufficiently large number of household-level brand purchases. The acceptable threshold will vary across product types, but in general, for frequently repurchased products, such as consumer packaged goods, a minimum of 18-24 months of past purchase history should be examined. On the other hand, infrequently repurchased products, such as automobiles or consumer electronics, may require all of the available purchase history to yield valid results. This means that in some cases there will not be sufficient amount of historical data to support robust analysis. A potential solution here is to sub-divide the buyer base into "classification-ready" and "classification-pending" groups, with the former containing all households that can be attributed with a sufficiently large number of purchases and the latter group holding households not yet meeting the number of category purchases requirements. The "classification-pending" segment can be proxy-analyzed with the help of the so-called "look-alike" analysis focusing on identification of high potential value customers with current high value brand buyers' based profile similarity.

Overall, the new, three-category loyalty classification logic better aligns loyalty analytics with data realities and it also relaxes the unrealistic repurchase exclusivity assumption. In doing so it emphasizes brand repurchase patterns over arbitrary "share of category" thresholds. It recognizes that households can be loyal to multiple brands and that continued brand repurchase is the ultimate manifestation of loyalty. Finally and probably most importantly, the expanded three-tier loyalty categorization minimizes potential buyer misclassification.

Incentive strategy

The second of the analytical priorities is an objective assessment of the treatment strategy. Once the retention targets have been identified and profiled with the help of robust customer valuation outlined above, the focus shifts to program economics. The most important components of the incentive strategy are:

- the monetary dimension capturing the economically-valued offer;
- frequency, which encapsulates the overall contact mix; and
- the messaging dimension combining the content and creative aspects of the incentive strategy.

Table I shows a treatment strategy planning framework built around the assessment of the expected impact of the components' components. Leveraging empirical results derived from a cross-section of direct (mail and e-mail) consumer programs, the resultant 3×3 matrix spells out the expected impact of the monetary, frequency and messaging elements of the contact strategy on customer repurchase rate, program cost and the potential implementation complexity.

The monetarily-valued offer has the greatest potential impact on repurchase rate, but can be expensive in terms of added cost. It can take many forms such as money-off coupons, free product sample, a fee waiver, a preferential

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Table I Generalized treatment strategy effects

		Impact on program	
Treatment components	**Potential repurchase rate improvement**	**Potential impact on cost**	**Potential implementation complexity**
Monetary (offer)	High	Increase	Low
Frequency (contact mix)	Low-medium	Maintain/decrease	Medium
Messaging (creative design)	Low-medium	Increase	Medium-high

treatment or service upgrades. For example, airlines use "bonus miles", hotels reward frequent travelers with room and service upgrades, some credit cards give their customers "cash back" and retailers rely on anything from "instant discounts" to free merchandise. A potentially high cost of these upgrades mandates differential treatment, to limit those offers whose customers' profit contribution warrants that level of investment (i.e. the importance of customer valuation). Ideally, the monetary value of an incentive should be based on either the current or expected future value of the customer to keep program economics on the right track.

The frequency of customer promotions is another important element of the program strategy. Although it can positively impact repurchase, an even more significant benefit to optimizing the frequency of communication is the potential cost saving. For example, a major bank used to contact each new customer eight times with cross- and up-sell offers, but with the help of response pattern analyses realized that in most cases four contacts were optimal. Cutting back on the number of mailings allowed it reallocate some of the promotional funds into higher impact areas, thus increasing the overall productivity of its marketing mix. As shown in Table I, the frequency dimension has a comparatively modest impact on stimulating repurchase rates but has a considerable potential to decrease the overall program cost. It is usually more complex to implement than the monetary dimension, primarily because it may entail a more involved customer treatment matrix.

Finally, the creative contact strategy dimension, which encapsulates the "look and feel" of the promotional materials, typically yields the least amount of directly attributable impact on loyalty initiatives' economics. That is not to say that the messaging dimension is not important—it is simply not as effective at driving sales incrementality as the other two offer strategy components. Changing it, however, can be costly primarily due to the labor-intensive nature of the redesign work; there is also a tendency to migrate from low cost single page direct mailers or text only e-mail messages to higher cost dimensional mailings (e.g. a high quality box containing numerous promotional materials) or more interactive, design richer e-mail options. Naturally, implementation complexities can be considerable.

Table II offers a concise summary of the expected effects and supporting justification.

Program impact measurement

The final of the top three analytical priorities is the development of a robust impact measurement methodology, one that is capable of quantifying treatment-attributable incrementality. Unlike the previously discussed front-end planning and incentive assessments, this is a back-end function intended to capture the impact of the program on an ongoing basis to support improvement recommendations.

Depending on the available data and treatment restrictions, such as the requirement of extending credit-related offers to all customers whose credit was queried, one of several impact measurement options might be selected. Table III presents a summary of the available options.

In general, the all-around most effective method of quantifying treatment-induced purchase incrementality is experimentation. It supports the most effective means of controlling for potentially confounding extraneous influences, thus yielding the cleanest, most reliable quantification of impact. The reason it is not always used is that it is also the most demanding, specifically in terms of the sampling frame and treatment rule requirements. The need to set aside a control group can lead to perceived opportunity loss of not marketing to a group of otherwise qualified prospects; in other instances, control groups cannot be set any aside because of credit queries mandating a requirement of making a credit-related offer. Even if an organization is willing and able to set aside a control group, the treated vs control groups' size or the overall sample composition can fall short of technical requirements, precipitating the confounding of treated with non-experimentally controlled factors. In the end, although experimentation has the potential to provide the most accurate assessment of program's effectiveness, it will not be a viable option for some organizations or situations.

Where experimentation is not an option, the statistical baseline might be a viable alternative. As outlined above, its requirements are considerably different, somewhat complementary to those of experimentation, making it a good substitute for situations where setting up experiments is not feasible. For example, the statistical baseline does not require setting aside control groups nor does it carry any treatment-related sampling requirements. On the other hand, it does require a sufficient amount of historical data and an a priori development of a statistical model. Its key advantage is the emphasis on standardization of cross-treatment effects, longitudinal consistency and low maintenance reusability.

Finally, in some situations a consumer survey based approach has also been used. Relying on buyer recall and rarely able to account for a number of macro factors, this is by far the least accurate method of quantifying treatment-attributable incrementality. As a matter of fact, it should only be used in situations where neither experimentation nor the statistical baseline can be deployed.

Some parting thoughts

A strong value proposition is not always sufficient to turn a loyalty initiative into a profitable business asset. For reasons ranging from runaway program costs to poor sales gains, unique and well-received loyalty offerings can fall short of their business goals. In this article, I argue that good loyalty ideas often struggle economically because of poor program planning and inadequate informational supports.

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Table II Purchase behavior impact of the treatment strategy components

Facet	Expected impact	Justification
Monetary	Impacts repurchase propensity by reducing acquisition costs ↳Strongest expected impact	Demonstrated above average price elasticity of demand
Frequency	Impacts repurchase propensity by amplifying potential costs ↳Second strongest expected impact	Additional touches lead to additional sales
Messaging	Impacts repurchase propensity by effecting the perceived cost-benefit relation ↳The weakest expected impact	Requires relatively high reader involvement

Table III Summary of program impact measurement alternatives

	Experimentation	Statistical baseline	Consumer survey
Type	Snapshot in time	Ongoing	Snapshot in time
Focus	Objective count of actual purchases	Objective count of actual purchases	Consumer recall of purchase drivers
General description	Approach built around treated and control groups Non-treatment specific differences randomized or blocked to avoid confounding Impact of treatment: incrementality = (treated − control)	Multivariate statistical model leveraging historical purchases and promotional data Models "unpromoted level of sales to be contrasted with actual sales Singles out multiple promotion specific effects and calibrates their respective elasticities	A sample of consumers surveyed via telephone, or e-mail or other means Probes product purchase intentions or reasons for purchase Relies on consumer recall of purchase reasons rather than actual purchases
Requirements	Conceptual experimental design Test and sampling plan, target-offer conjoints Measurement plan Willingness to set aside control groups	A minimum of 18 months of past purchase and promotional data A multivariate statistical model Periodic refresh of the model	Recency of customer behaviors Measurement instrument Decision rules to translate consumer opinions into quantifiable behaviors
Strengths	Purchase-based, measuring actual sales Unbiased and objective Capable of attributing incrementality to specific promotions or other actions No responder or measurement bias	Purchase-based, objective and unbiased Quantifies effects of multiple promotions concurrently Ideal for cross-time comparisons and trending Very low long terms cost	Does not require setting aside control groups or a priori statistical models Can yield consumer insights Does not require pre-program planning
Weaknesses	Requires setting aside untreated control groups Depends on robust pre-program launch planning Difficult to factor-in external macro factors, such competitive activity	Requires development of possibly complex statistical model Too complex for one-shot programs	Relies on consumer recall for purchase attribution Biased (poor recall, demand effect) Does not account for macro factors High recurring cost
Usage situations	*Ad hoc* programs with well-defined offer Special interest elements with ongoing programs	Ongoing programs requiring consistent measurement of impact	Programs where experimentation or statistical baseline cannot be used

Planning is often focused almost exclusively on operational, program launch related decisions, which while important in their own right do not expressly address the fundamental relationship between the anticipated program costs and benefits. Furthermore, a number of tactical decisions are made outside of an appropriate strategic context. For instance, participant recruitment decisions are rarely made in a broader context of the revenue vs. profit contribution.

Program planning is also frequently hampered by informational deficiencies. Often "data rich, but information poor", loyalty initiatives are notorious for under-leveraging the data otherwise readily available to them. In addition, some of the underlying analytical processes are overly simplistic, sometimes to the point of being misleading, as exemplified by the buyer loyalty categorization heuristic. Overlooking the critically important purchase data householding and the resultant pooling of individual product needs, this customer classification approach is switcher-biased. Taking into account data householding and explicitly factoring-in household-level assessment of category purchase requirements enables a more robust three-way loyalty classification system, replacing the less reliable loyal-switcher dichotomy.

Overall, the ideas presented in this article focus on economics of loyalty initiatives. They are intended to help to grow great loyalty ideas into profitable business assets. They are also intended to contribute to tactical decision making by placing those decisions in a larger, end outcome oriented, set of business considerations.

Notes

1. A treatment is defined as any loyalty program-originated communication, offer or incentive intended to stimulate purchase.
2. For more detail see Banasiewicz (2004).
3. For example, barcoded transactional data tends to be organized around the product-store-time continuum; consumer surveys are organized around individual

responders and marketing program responses are event-based.

4 Specifically, it requires a customer-level quantification of transactional profitability and repurchase propensity to identify high value buyers.
5 Product category is comprised of all brands offering functionally substitutable products; for instance, all ready-to-eat breakfast cereal brands comprise the ready-to-eat breakfast cereal product category.
6 Although at least some of the transactional information is collected at the individual consumer level, the database de-duplicating (redundant record cleansing) and aggregating (rolling up of individual transactions to total value) processes effectively transform individual into household level information. In addition, third-party overlay data (e.g. geo-demographics, lifestyle, etc.) is usually only available at a household or even a more aggregate level.

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Executive summary and implications for managers and executive readers

This summary has been provided to allow managers and executives a rapid appreciation of the content of this issue. Those with a particular interest in the topics covered may then read the article in toto *to take advantage of the more comprehensive description of the research undertaken and its results to get the full benefit of the material present.*

Loyalty schemes – a lesson in basic direct marketing

In order to consider the implications of Banasiewicz's research, it might help to begin with being polemical in describing the marketing profession. On one hand are the artists – concerned with the imagery, creativity and style of marketing – and set against them are the scientists – hunched over their pages of numbers, worrying about analysis. Now I know that this roundheads and cavaliers description of us marketers is a little wide of the mark since we know it is possible to be concerned with matters of art and science! However, what Banasiewicz castigates is the failure to remember those good old direct marketing basics when it comes to the strategic application of databases and relationship marketing.

Banasiewicz's starting point is that too many loyalty programs fail to live up to their billing. As our author puts it, "... in spite of their promise and growing popularity, many buyer loyalty programs become financial liabilities instead of self-funding business assets" And the reason for this? First, inadequate program planning and secondly, insufficient customer insights.

The result of this is that we end up giving customers willing to pay at full price a discount, we do not recruit any new customers and we do not get additional sales off the scheme. As a result of this failure many practicing marketers now line up to denounce loyalty schemes as expensive, unworkable – the database marketer's pipe dream. Banasiewicz suggests that if we got things right in the first place more of the schemes would succeed.

Get your objective right, measure the right things and target

There are two possible endings expected from a loyalty scheme – higher sales value or higher profits. You can't have both just one or the other. As Banasiewicz says "... avoid the temptation to pursue both goals simultaneously or you run the risk of missing both targets".

So which should we go for? Look at your overall position in the market, at the stage the brand is in its life cycle and at the relationship with other brands. For me, instinct suggests go for higher profits (that is what you are there for, after all) but for newer brands increasing market share might be a worthwhile activity and a loyalty scheme just might provide the means.

So having picked just one clear objective what next? Get the "metrics" right which means measure things that actually relate to your objective. Banasiewicz criticizes the lazy approach of using registration as a key measure. As he puts it "... customer registration is a poor indicator of program performance because it relates the impact of the program to an activity that – by itself – delivers little or no economic value to the brand". Methinks Banasiewicz is letting us off lightly – all registration measures is how much it is going to cost us to run the program!

The metrics we use must relate to the objective, which means measuring actual sales or contribution gain ideally at the individual customer level. This measure will tell us how the loyalty scheme is working – whether the incentives offered to the customers are driving either more sales or else higher profits The information we want to know and it is on hand, just not quite as easy to gather as the numbers signed up to the scheme. Which brings us to who we should sign up in the first place.

Banasiewicz argues forcibly for targeting loyalty schemes. For the uninitiated this means that some of your current customers are not worthy of receiving the opportunity to join the scheme because they are not likely to buy more stuff from you as a result. Too many schemes fall over at this point because they use buyer self-selection to recruit. Banasiewicz points out that such an approach is easy to execute but argues that investing time and money in careful targeting will usually more than pay for itself in terms of sales gain.

Loyalty schemes mean active direct marketing not passive communications

It becomes clear from Banasiewicz's approach that loyalty schemes succeed where they get the incentives right. We want the customer to feel special and much-loved while, at the same time, spending more money at good margins with us. This requires us to understand loyalty at little better than we do at present – at least in the sales promotional context.

Banasiewicz sets out the dynamics of loyalty very clearly and demonstrates that a little bit of methodological due diligence pays dividends and I can recommend a careful appraisal of the presentation given here of what, in practical terms, constitutes loyalty. The concept of a household being "multi-brand loyal" is especially important since a moments

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thought (admittedly after reading Banaciewicz's analysis) reveals this to be pretty common-sensical – just think of breakfast cereal!

Beyond this you need to plan out the incentive strategy bearing in mind that monetary incentives are the most effective in response terms and the most expensive. What matters is that we are clear about the offers to be made, when they will be made and what they will cost us to deliver. This means that we are able to know (one of the direct marketing basics) how much it costs us to get a response and what impact this will have on the bottom line.

Finally we should consider how we manage and improve the performance of our loyalty scheme. Banasiewicz, rather kindly, describes three different ways of assessing the impact of the program – experimentation, baseline assessment and market research. For the good direct marketers, there should be only one option – experimentation. Or, as we were taught many years ago, set up a good control and test, test and test again.

It is good to see an article that focuses on oft ignore basics and especially on the main elements of a direct marketing program. Too often we get sucked into the wonders of new marketing schemes and lose sight of one basic principle – set clear objectives and design the program to deliver that objective. Oh, and test and measure performance all the time.

(A précis of the article "Loyalty program planning and analytics". Supplied by Marketing Consultants for Emerald.)

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