RFM Analysis Optimized

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Abstract

In the classic recency, frequency and monetary approach to market segmentation, i.e. RFM analysis, given a time frame, customers are clustered together into an arbitrary number of segments according to their most recent day of purchase, the number of purchases and the monetary value of their purchases. In this work we show how the choice of the number of segments and the time frame used in the RFM segmentation process can be optimized to maximize the result of direct marketing campaigns. We also indicate how RFM analysis can be extended to accommodate new dimensions of customer behavior and how the extended RFM analysis can be optimized. Furthermore, we discuss the implications of the optimized and extended RFM approach to market segmentation for direct marketing and business strategies.

Key words: RFM Analysis; Direct marketing; Market segmentation; Genetic algorithm; Data mining.

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1 Introduction

Despite all the skills, knowledge and experience that a direct marketing professional may have gained over the years and all the effort that he or she put into the preparation and rollout of a marketing campaign, there are always clients who don't make any purchase at all. Actually, when clients are directly target with an offer by a company, one should expect that only a small fraction of those clients will react favorably to the offer, placing a buying order, as a result [4,3,12].

Data and financial analysis on reported cases in the catalog industry indicate that profit tends to increase when companies decline to send communication to clients that are highly unlikely to make a purchase. On the other hand, for the same reasons, profit tends to increase when clients that are likely to make a purchase are targeted with offers that match their preferences and habits, receive customized introduction letters, are subjected to well conceive reminder messages and, if everything else has failed, are sent an additional full package of communication material [13,2].

Therefore, it is crucial for the financial success of a direct marketing campaign that marketing professionals have some insight into the profile of clients that are likely and unlikely to make purchases. Surprisingly, direct marketing professional have been trying to gain such insight since the end of the 19th century, when the Butler's bothers pioneered the catalog business industry, launching Our Drummer, the first catalog of products that could be ordered by mail, in the USA [20]. However, it was only in the beginning of the 60s that George S. Cullinan devised a simple and effective quantitative method to separate clients that are likely to make purchases from those that are not. He called his method the recency-frequency-monetary analysis or RFM for short [11].

Given a time frame and a client database, the method requires the computation of three different figures for each client: their most recent day of purchase, the number of buying orders they have placed and the total monetary value of their purchases. These figures are the client's recency, frequency and monetary value.

Next, clients should be clustered together according to these figures. Initially, clients are clustered into segments of equal size according to their recency. Subsequently, clients in each of the recency segments are further divided into new segments of equal size according the number of buying orders. Finally, the new segments are divided once again into a newer set of segments according to the monetary value of their purchases. The number of segments in each step of the segmentation process is arbitrary.

According to Cullinan, *op. cit.*, experience repeatedly shows that clients who have purchased one or more products recently, place buying orders frequently and spend a considerable amount of money with a company, within a time frame, are more likely to make new purchases in the near future. Moreover, clients that haven't purchases products for quite sometime, place buying orders occasionally and spend a small amount of money with a company are less likely to place a buying order in the future.

Although simple, Cullinan's RFM analysis has proved to be a valuable tool for direct marketing professional. Its effectiveness has been widely reported; it is easy to understand and does not require from their users a deep knowledge of either mathematics or statistics [3,7,21,1]. Furthermore, detailed description of RFM analysis can be found in a number of easy-to-read books [18,17,26], the information required by the method is frequently available in most client databases at very low additional cost and it can be easily implemented in a spreadsheet [27]

In this article we present evidence that challenges two main assumptions generally made by RFM users, i.e. the order in which the dimensions recency, frequency and monetary value are applied in the segmentation process is immutable, i.e. it doesn't depend on the industry or line of business, and the number of segments in each dimension can be chosen arbitrarily without considerable financial consequences. Also, we show how the time frame required by the method should be chosen to maximize the results of direct marketing campaigns. Furthermore, we present an RFM optimized model that yields better results than the classic RFM model and indicate how it could be expanded to include new dimensions and combined with other data analysis methods.

2 Conceptual Framework

The success Cullinan's RFM method among marketing professionals has prompted further investigation on the relevance of the recency, frequency and monetary-value dimensions to the forecast of repeated purchases in businesses that use direct marketing concepts and techniques, especially in the catalog industry.

Bob Stone, in *Successful Direct Marketing Methods*, a book that became quite popular among marketing professionals, claims that the use of a point system substantially improves the RFM efficiency [5,6]. Stone's point system requires RFM data to be collect over a twelve-month period. Clients that have made a purchase in the current quarter are granted 24 points in the recency dimension. If they have made purchases in the previous quarter, they are granted an extra 12 points, in quarter before that an extra 6 points and an extra 3 points in the quarter before. Points in the frequency dimension are granted multiplying the number of purchases in the twelve-month period by four. In the monetary dimension, the number of point is calculated multiplying 0.1 by the total amount of money spend by the client within the same time frame, limited to a maximum of 9 points.

Robert D. Kestnbaum, CEO of the Kestnbaum & Company, is credited to be the first to propose the addition of a new dimension to the RFM method, i.e. the type of products that were last bought by each client. Also, he pioneered the use of the RFM dimensions in a different order in the segmentation process. He called FRAT his RFM modified method. In FRAT analysis the frequency dimension comes first in the segmentation process Stone, [5,6].

Authur M. Hughes, in *Strategic Database Marketing*, ignores Stone's point system for RFM analysis and suggests that each RFM dimension should further divide the current segments in the client database into five new segments. At the beginning of Hughes' RFM segmentation process there is only one large segment in the database, which contains all clients to be targeted by a marketing campaign. In the end of the segmentation process, one ends up with 225 ($5 \times 5 \times 5$) different segments [18].

Hughes, *op. cit.*, and Miglautsch [12] wisely point out that although the RFM method works well with customer's databases, in both the customer-to-business and business-to-business market segments, it should be used with neither prospects nor first time buyer data, because the method was conceived to work efficiently on data from client with a prior purchase history.

Miglautsch, *op. cit.*, goes further and warns that RFM analysis tends to overshadow the potential financial earning yielded by clients who haven't placed buying order for quite sometime, rarely place an order and have low mean ticket value. It should be noted that, in many circumstances, this is by far the largest segment in client databases. However, he indicates that such limitations can be overcome with the introduction of three different classes of variables: customer lifestyle, geodemographic information and population density over a variety of discrete variables such as postal code and industry classification.

Recent research in the data analysis and modeling methods suggest that better results can be obtained by combining methods that exploit unrelated dimensions of the same dataset. Sung and Sang [10] uses the RFM dimensions, Kohonen's [24] self-organizing map and Quinlan's [22] C4.5 classification trees to improve the turnover of a duty free shop. Suh *et al.* [9] successfully combines RFM analysis with neural networks and logistic regression to estimate the financial results of direct marketing campaigns. Following a similar line of research Baesens *et al.* [3] uses an enriched RFM model and Bayesian neural networks to forecast purchases for a European direct mail company.

Ansari et al. [23] widens the scope of RFM analysis, using it to evaluate customer churns and profitability. Shih [27] widens the scope even further, using Stone's RFM point system to calculate customers lifetime value (CLV) in the hardware retail industry. Shih starts out making the assumption that the points granted to each RFM analysis varies across different industries. Thus, expert opinion and the hierarchical analytical process present in [15] are used to establish the points to be grated to each RFM dimension. Next, clients are clustered into segments according to the RFM normalized variables. Finally, the CLV of each cluster is calculated.

3 Method

In order to achieve the results presented in this article, data from real-world direct-marketing campaigns have been examined under three different scenarios. The first considers the results yielded by those campaigns without the use of any forecasting methods. The second examines the results that would have been yielded with the support of Hughes' RFM model. Finally, the third evaluates the results that would have been accomplished with the help of RFM optimized models.

The data used in the scope of this article has been kindly provided by two large companies: a retail chain store, which sells household appliances and furniture, and a virtual department store. While the retail chain store does most of its business in the mortar and brick world, the department store sells its products and services in the virtual world alone. From now on, these companies are called X and Y Companies respectively.

Both the X and Y Companies provided large amount of data about one of their direct marketing campaigns containing information about clients, the products they have bought in the course of time, their respective selling price and whether they have made a purchase or not as a result of a specific direct marketing campaign. In these campaigns the X and Y Companies have declined to use RFM analysis. As a result, all potential targets have been subjected to an offer. While the X Company sent its offer by regular mail, the Y Company used e-mail.

Throughout the article, data from the X Company is used to access the contribution that the RFM optimized model may potentially provide towards the financial results of direct marketing campaigns. On its turn, data from the Y Company is used to discuss the strong relationship that exists between the model usefulness and a company's direct marketing strategy.

The RFM models presented in this article were built with the help of a popular spreadsheet software and an all-purpose optimization tool. The former is the Excel spreadsheet 2002, from the Microsoft Corporation (www.microsoft.com), and the latter from the Evolver for Excel 4.0, from the Palisade Corporation (www.palisade.com).

Evolver is an add-in to Excel, which allows users to build optimization models using the features provided by the Excel spreadsheet in addition to special features provided by the tool (Palisade, 2001). Therefore, an Evolver spreadsheet is actually an optimization model, which contains:

- Equations which bind together variables and constants,
- Variables whose values might be adjusted during the optimization process,
- Constraints that restrict the values that adjustable variables may take,
- A numerical target which specify what is expected from the optimization algorithm,
- A fitness function which figures the degree of fitness of each candidate solution to the model, and
- Stopping rules which indicate when the optimization algorithm should stop looking for better solutions.

Because our main concern is with the maximization of the financial results yielded by the RFM analysis, the Evolver model we built has the following adjustable variables:

- The order in which the dimensions recency, frequency and monetary value are considered in the analysis process;
- The time period in which recency, frequency and monetary data are collected and
- The number of segments into which the recency, frequency and monetary dimensions are divided up.

The fitness function we designed calculates the financial result yielded with the support of an RFM model, which becomes increasingly better in the course of the interactions carried out by the optimizations engine. As a stopping rule we set the optimization engine to keep looking for better solutions to the model while the current solution provide an improvement of at least 1% over all the previous 200 attempts.

Evolver solves optimization problems using genetic algorithms, a family of optimization methods that searches for the best solution of a problem mimicking the process found in natural evolution. The genetic algorithm paradigm is due to Holland [8]. An introduction to genetic algorithm concepts and techniques is found in [19]. A step-by-step introduction to Evolver is presented in [16].

3.2 The X Company: Doing Business in the Real World

Founded in the late 40s, in Rio de Janeiro, the X Company is one of the biggest and oldest chains of electrical-appliances stores in operation in Brazil. Besides electrical appliances, the X Company sells also a complete array of home furniture, ranging from simple chairs to kitchen cupboards, and computer hardware for both home and home office environments.

In 1996, with the view of increasing its growth pace, the X Company opened its capital to public participation through a combined offer of shares, in the São Paulo stock exchange, American depositary receipts [1] (ADRs), in the New York Stock exchange, and Euronotes [2], in European market place. Nowadays, the X Company has over 340 stores in ten of the economically most important Brazilian states. Table I presents some main statistics about the X Company.

Main Figures (USD)	**2002**	**2001**
Turnover (million)	900.3	867.3
Number of retail stores	346	348
Number of employees	8,370	7,409
Liquid assets (million)	187.0	182.3
Profit (million)	11.9	13.0

Table I: X Company's main figures

In order to make it easier for customers, the X Company has made available two alternative sales channels to its brick and mortar chain of retail stores, i.e. a receptive call center, which allow orders to be placed over the phone, and an Internet site for e-commerce, where customers can browse through its catalog of products, obtain detailed information about what is for sale and ask questions to sales representatives before making up their minds. All of this is an impressive set of achievements for a company that started up 52 ago, with a single store in Rio de Janeiro downtown.

[1] Documents (receipts) representing shares owned by US citizens in an overseas company. The receipts are tradable and the shareholder is entitled to dividends paid by the issuer of the shares. ADRs are a convenient way for non-US companies to issue equity in the US.
[2] Euronotes are short-term bonds underwritten by an international syndicate. They are usually sold in countries other than the country of the currency in which the issue is denominated.

The database provided by the X Company contains 128,354 observations of purchases made between January 2000 and October 2002 by 50,529 clients targeted by one of their direct marketing campaigns; only 985 clients made a purchase as a result of this campaign, i.e. 1.95% of the targeted clients. Table III summarizes the results of this campaign.

Campaign Data	**X Company**
Targeted population (clients)	50,529
Clients in the targeted population who placed buying orders	985 (1.95%)
Communication cost per client	USD 0.94
Total communication cost	USD 47,497.26
Turnover	USD 68,769.84
Profit (Turnover - Total communication cost)	USD 21,272.58

Table III: Statistics on the X Company's direct marketing campaign

According to Hughes (2000) RFM analysis starts up by clustering potential targets of a direct marketing campaign into 225 segments of equal size. Next, client in a sample taken from the database are subjected to an offer of products and services. Afterwards, the reaction of clients in the sample is used to estimate the future reaction of each of the 225 segments of potential targets to the same offer. Segments that yield financial results bellow the break even point are not to be targeted by a direct marketing campaign. All of this aims at improving the financial results of direct marketing campaigns. Table IV summarizes the results of the X Company's direct marketing campaigns, if Hughes' RFM model had been used considering a typical timeframe of 2 years.

The Optimized RFM model allows the different dimensions to be applied in a different order. Also, the number of segments in each dimension may vary together with the timeframe under consideration. Table IV summarizes the configuration of the RFM different parameters yielded by the optimization process. Table V summarizes the results of the X Company's direct marketing campaign, if the RFM Optimized model had been used.

Graphic I presents a summary of the financial earnings provided by the direct marketing campaigns in the three situations considered in the scope of this article, i.e. the X company declines to used RFM analysis, Hughes' RFM model is used and the RFM Optimized model is used.

Campaign Data		**X Company**
Target population (clients)	Sample Test	3,000
	Rollout	29,030
	Total	32,030
Clients who placed buying orders within targeted population	Sample Test	65 (2.2%)
	Rollout	716 (2.5%)
	Total	781 (2.4%)
Communication cost per client	Sample Test	USD 0.94
	Rollout	USD 0.94
Total communication cost	Sample Test	USD 2,820.00
	Rollout	USD 27,288.20
	Total	USD 30,101.20
Turnover	Sample Test	USD 4,270.60
	Rollout	USD 56,118.45
	Total	USD 60.389,05
Profit (Turnover - Total communication cost)		USD 30,287.85

Table IV: Statistics on the X Company's direct marketing campaign, if Hughes' RFM model had been used.

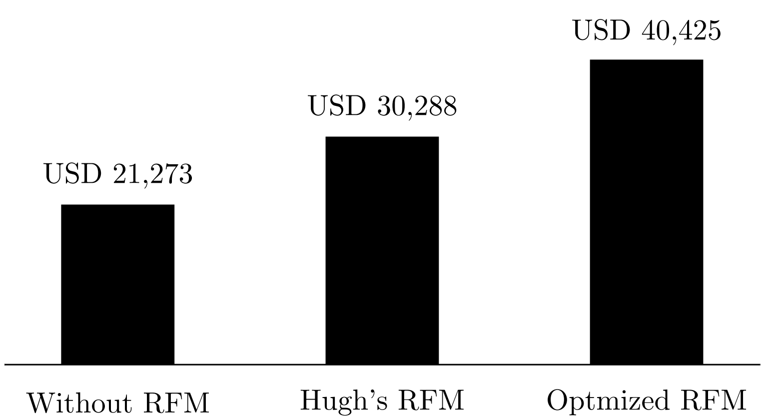
Campaign Data (sample test and rollout)	**X Company**
Number of recency segments	8
Number of frequency segments	5
Number of monetary value segments	17
Order in which the segments are applied	FMR
Timeframe under consideration	830 days

Table V: Statistics on the configuration of the X Company's direct marketing campaign, if the RFM Optimized model had been used.

Its is important to mention that at the time this article was finished, the X Company was running 6 direct marketing campaigns yearly. Face the good results provided by their direct marketing campaigns, they had plans to run at least one campaign a month. Therefore, the annual financial impact of the RFM Optimized model on the profit of the direct marketing efforts of the X Company could be quite considerable.

Campaign Data		X Company
Target population (clients)	Sample Test	3,000
	Rollout	21,224
	Total	27,224
Clients who placed buying orders within targeted population	Sample Test	65 (2.2%)
	Rollout	703 (3.3%)
	Total	768 (2.8%)
Communication cost per client	Sample Test	USD 0.94
	Rollout	USD 0.94
Total communication cost	Sample Test	USD 2,820.00
	Rollout	USD 19,950.56
	Total	USD 22,770.56
Turnover	Sample Test	USD 4,270.60
	Rollout	USD 58.925.11
	Total	USD 63,195.71
Profit (Turnover - Total communication cost)		USD 40,425.15

Table IV: Statistics on the X Company's direct marketing campaign, if the RFM optimized model had been used.



Graphic I: Profit earnable by the X Company under different circumstances.

3.4 The Y Company: Doing Business in the Virtual World

The Y Company is a virtual department store and one of the pioneers in e-commerce in Brazil. Its catalog of over 3,000 products displays household appliances, personal computers, computer accessories, cameras, stereo equipment, DVD players, workshop tools, beauty care products, jewelry, books, games etc. Since it went in business in 1995, the Y Company has experience annual growth of over 20%, earning important market space in the business-to-consumer (B2C) segment. In 2001, its turnover exceeded USD 32 million. Table VI presents some important figures about the Y Company.

Main Figures	**2001**
Turnover (million)	USD 32.1
Clients in the company's database (million)	2.3
Number of daily buying orders	1,630
Mean ticket value	USD 83.3

Table VI: Y Company's main figures

3.5 The Y Company: The Experiment and Their Results

The database provided by the Y Company contains 105,577 observations of purchases made between December 2000 and March 2004 by 59,529 clients targeted by a direct marketing campaign; a total of 639 clients have placed buying orders as a result of this campaign, i.e. 1.07% of the targeted clients. Table VII summarizes the results of this campaign.

Campaign Data	**Y Company**
Targeted population (clients)	46,180
Clients in the targeted population who placed buying orders	654 (1.41%)
Communication cost per client	USD 0.17
Total communication cost	USD 7,850.60
Turnover	USD 83,150.54
Profit (Turnover - Total communication cost)	USD 75,299.94

Table VII: Statistics on the Y Company direct marketing campaign

Table VIII summarizes the configuration of the RFM different parameters yielded by the optimization process. Table XIX summarizes the results of the X Company's direct marketing campaign, if the RFM Optimized model had been used.

Graphic II presents a summary of the financial earnings provided by the direct marketing campaigns in the three situations considered in the scope of this

Campaign Data (sample test and rollout)	**Y Company**
Number of recency segments	6
Number of frequency segments	8
Number of monetary value segments	6
Order in which the segments are applied	FRM
Timeframe under consideration	135 days

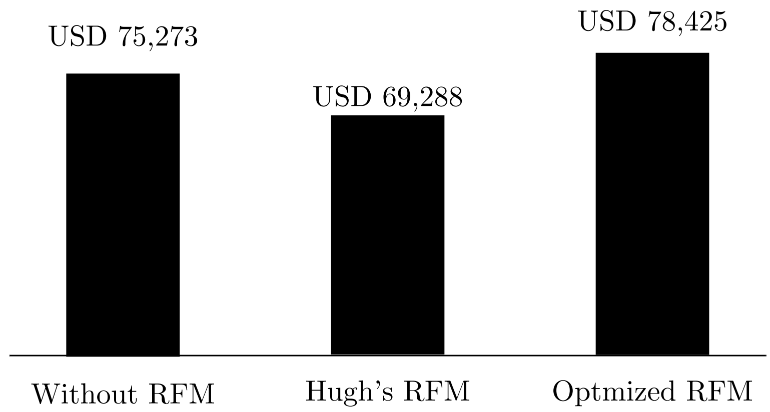
Table V: Statistics on the configuration of the Y Company direct marketing campaign, if the RFM Optimized model had been used.

Campaign Data		**Y Company**
Target population (clients)	Sample Test	3,000
	Rollout	22,775
	Total	25,775
Clients who placed buying orders within targeted population	Sample Test	48 (1.6%)
	Rollout	517 (2.3%)
	Total	565 (2.2%)
Communication cost per client	Sample Test	USD 0.17
	Rollout	USD 0.17
Total communication cost	Sample Test	USD 510.00
	Rollout	USD 3,871.75
	Total	USD 4,381.75
Turnover	Sample Test	USD 5,843.79
	Rollout	USD 67,605.83
	Total	USD 73,449.62
Profit (Turnover - Total communication cost)		USD 69,067.87

Table IV: Statistics on the X and Y Companies' direct marketing campaign, if Hughes' RFM model had been used.

article, i.e. the Y company declines to used RFM analysis, Hughes' RFM model is used and the RFM Optimized model is used.

At the time this article was finished, the Y Company was was running over 140 e-mail campaigns. Therefore, the small improvement in financial results provided by the RFM Optimized model for a specific campaign may still result in a meaningful annual contribution in financial terms to the direct marketing efforts of a company.



Graphic II: Profit earnable by the Y Company under different circumstances.

4 Discussion

At the outset of this article we undertook to answer a set of key questions. The answers are presented below:

4.1 Why should the RFM analysis be optimized?

The RFM analysis is one of the most popular customer segmentation methods among direct marketing professionals. The concepts underlying the method are easily mastered, even by those with little background on mathematics and statistics. Moreover, the implementation of an RFM model does not require any expensive piece of equipment or software. Most RFM implementations can be done with the help of a regular personal computer and inexpensive spreadsheet software. As a result, by showing how RFM analysis can be optimized we not only extend the capabilities of a popular method, but we also benefit customers, direct marketing professionals and companies of all sizes worldwide.

4.2 How is this optimization accomplished?

The classic RFM model requires that a series of arbitrary decisions are made by direct marketing professionals and their managers. For example, the customers to be targeted by the marketing campaign, the offer to be made to those customers, the timeframe to be considered to collect customer data, the number of segments in each RFM dimension, i.e., recency, frequency and monetary value, the order in which these dimensions are applied, the rollout date of the marketing campaign etc.

Obviously, such decisions are bound to have a considerable impact on the results of any marketing campaign. In the absence of a mathematical model to find the proper combination of parameters that maximizes the results of a marketing campaign, many direct marketing professionals solely rely on past experience and intuition to make those decisions. This may easily lead to poor financial results and reduced customer satisfaction.

The RFM optimized model offers direct marketing professionals the possibility of setting up some of the parameters required by the classic RFM model in such a way that the results of marketing campaigns are maximized. These parameters are: the data collection timeframe, the order in which each RFM dimension should be applied and also the number of segments to be used in each dimension.

Moreover, the RFM optimized model allows for the introduction of new dimensions such as last product or serviced purchased by customers and their preferred line of products. This is done in a way that maximizes even further the results of a direct marketing campaign. In this case, the order in which each new dimension should be applied and the number of segments into which clients should be organized according to the amount of money they have spent in each product line will help to determine the likelihood of clients making a purchase.

4.3 How does the RFM optimized model maximize the results of direct marketing campaigns?

In order to make direct marketing campaigns more profitable the classic RFM model clusters the customers of a company into segments according to the recency of the last purchase they have made and frequency and monetary value of their purchases. A sample is then extracted from the clustered segments and targeted with an offer. The way in which customer react to that specific offer allows for the withdrawing of segments that are expected to fall short of reaching the campaign breakeven point.

What the RFM optimized model does is to identify much more precisely than the classic RFM approach the segments that are likely to fall short of the breakeven point. The order in which the dimensions of the RFM are applied (RFM, FRM, MRF etc.), the number of segments in each of these dimensions and the timeframe are calculated to allow for the withdrawing of the optimum number of segments that maximizes the campaign results.

It should be noticed that, in the general case, any given segment is composed of both customers who are expected to react favourably to the offer being made and customers who are not. In this sense, what the optimized RFM model does is to figure the number of segments that better separates one kind of customers from the other.

4.4 How can the RFM optimized model be used to determine more precisely the profile of customers to be targeted by direct marketing campaigns?

The classical RFM model makes the assumption that an effective way of analyzing client behavior with respect to direct marketing campaign is to put them into segments according to their most recent day of purchase, the number of purchases within a certain period and the monetary value of their purchases. Furthermore, many direct marketing professionals keep track of clients that are constantly clustered into the most valuable segments as a way of identifying their most important clients. In many cases such clients are targeted in additional marketing campaigns aimed at better satisfying their needs.

Although the results presented in this article do not disprove this assumption, it shows a more effective way of using the ideas underlying the RFM analysis. By figuring out the optimum way of organizing clients into segments, the RFM optimized model provides a more accurate insight into the behavior profile of clients and yields a more precise way of identifying our most valuable clients.

4.5 What is the expected impact of the RFM optimized model on both business and marketing strategies?

The more profitable direct marketing campaigns yielded by the RFM optimized model favours the use of direct marketing concepts and techniques. Because the use direct marketing requires a better knowledge of client's profiles, the RFM optimized model motivates companies to better know their clients, creating opportunities for the development of products and services that better serve their needs.

4.6 How can customers benefit from the RFM optimized model?

The RFM optimized model allows companies to send marketing campaign communication only to segments of consumers that are likely to make purchases. This tends to improve customer's satisfaction with the communication they receive, with positive impact on a company's image in their clients' mind. In addition, by sending less communication, company's expenditure on marketing campaigns is substantially reduced. If the market where a company sells its products is competitive, then, sooner or later, such reduction on cost

Main Figures (USD)	2001
Turnover (million)	32.1
Clients in the company's database (million)	2.3
Number of daily buying orders	1,630
Mean ticket value	83,3

Table II: Y Company's main figures

leads to either better prices for consumers or more products and services for the same price.

Moreover, the RFM optimized model favors better financial results for direct marketing campaigns, yielding higher profit margins for companies. Profitable companies tend to remain in business for a longer, providing valuable products and services for their customers.

4.7 Does the Usefulness of the RFM Optmized Model Depend on the Company's Direct Marketing Srategy?

The Y Company is a virtual department store and one of the pioneers in e-commerce in Brazil. Its catalog of over 3,000 products displays household appliances, personal computers, computer accessories, cameras, stereo equipment, DVD players, workshop tools, beauty care products, jewelry, books, games etc. Since it went in business in 1995, the Y Company has experience annual growth of over 20earning important market space in the business-to-consumer (B2C) segment. In 2001, its turnover exceeded USD 32 million.

The Y Company's client database contains records of over 2 million consumers, who are frequently targeted with offer of product and services via e-mail. More than 80middle and upper echelon of the Brazilian society. This yields over 1,600 buying orders daily with a mean ticket value of USD 83.30. Table II presents a summary of these figures.

5 Conclusions

RFM analysis is valuable and popular tool to improve financial results and client satisfaction with direct marketing campaigns, which yields a positive impact on the way companies relate to their customers. By more precisely estimating the likelihood of each client making a purchase, the RFM optimized model increases the financial results of direct marketing campaigns, help to identify more precisely our most valuable clients and improves the quality of communication between companies and their clients. All of this helps organizations to become more efficient, competitive and profitable, and stay in business for a longer. Moreover, the optimized RFM model favours the use of direct marketing concepts and techniques, providing a better insight on customer behaviour.

The RFM optimized model is a new contribution to direct and relationship marketing, which yields a positive impact on the way companies relate to their clients. This impact has both a qualitative and a quantitative nature. Its qualitative nature stems from the fact that the optimized model motivates companies to send marketing communication only to clients that are likely to make purchases and that, as a result, will value the offers made to them. The quantitative nature is due to the cost reduction that it provides by preventing companies from wasting money on clients that are unlikely to make any purchase at all. Money saved on useless communication might be used in new marketing campaigns, which offer products that are better suited to the clients they target. All of this is accomplished in an optimum way.

Finally, by optimally adjusting the different dimensions of the RFM analysis, the optimized model reduces the risk of running unsuccessful direct marketing campaigns, making marketing professionals more confident in including direct marketing concepts in the overall marketing strategy of their companies. Also, the RFM optimized model allow for the introduction of new dimensions such as last purchased made by clients and their preferences for different product lines, making the results yielded by the model even more accurate.

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