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An Exploratory Study to Improve Sales Operations When Selling Multiple Prescription Drugs

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An Exploratory Study to Improve Sales Operations When Selling Multiple Prescription Drugs

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This paper explores the importance of integrating knowledge with quantitative modeling process to improve sales operations in multiple product selling situations in the pharmaceutical industry. A knowledge-based approach is proposed to minimize challenges in detailing multiple products to physicians who are more and more difficult accessing in recent years. The performance of this new approach is compared against the traditional approach via actual implementation by the firm that is sponsoring the research. Results based on three months of implementation indicate that the knowledge-based approach performs significantly better with increasing the number of responsive physicians by 71% and profit by 9%.

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I. INTRODUCTION

The pharmaceutical industry has faced a number of challenges in the recent years, with many branded drugs going off patent without enough blockbuster drugs in the pipeline to replace them (PricewaterhouseCoopers, 2008). In addition, the industry has received a lot of negative press from both the government and consumers for the aggressive investment in to their sales and marketing efforts (Gagnon and Lexchin, 2008; Washington Post, 2002). Obviously, the industry needs to find a way to better utilize their sales and marketing spending to fend off some of these challenges.

Sales force is the most expensive marketing investment that a pharmaceutical company can make. The primary function of sales force is to provide detailing to their target physicians. The target physicians are those who already prescribe or have potential to prescribe the firm's prescription drugs; detailing involves pharmaceutical sales representatives visiting each of their physicians to disseminate the latest information on the firm's prescription drugs that is meaningful to the physician's specialty and the patients he or she is treating. The detailing is done with the goal of encouraging the physician to correctly prescribe the firm's drugs for those patients who fit the diagnostic criteria, and given a similar treatment situation where two prescription drugs are equal in providing help to patients, the firm assumes that the sales rep's selling capability would sway the physician to prescribe their product. With a heavy price tag of $150 to $200 per detail, companies put a significant effort into determining the right physicians to target, the order of the details, also known as detailing sequence, when multiple products are involved, and the frequency of details to the targeted physicians over time (Gagnon and Lexchin, 2008).

This paper explores the importance of a knowledge-based approach in improving sales force operations in multiple product detailing situations by integrating domain knowledge with quantitative modeling process. The approach specifically targets to minimize major limitations of the traditional approach in planning for detailing multiple products. The result from this study is implemented and tested in a real-world environment to a sample of physicians in a territory to explore its performance against a control group of similar physician size and sales volume.

The remainder of the paper is organized as follows: Section II gives an overview of the background of the pharmaceutical industry and sales operations related challenges taking place in the industry. Section III explains the data sets used for this study. Section IV describes a knowledge-based approach developed to derive a set of weights for planning detailing strategy, and Section V summarizes the plan's performance based on actual implementation of the approach. Section VI discusses the approach and concluding remarks.

II. BACKGROUND OF THE INDUSTRY

Physician detailing is the primary means to market pharmaceutical drugs because in this market the physicians are the ones who decide the best treatment algorithm for their patients, who are the end users. This dynamic of promoting to physicians, is different from traditional marketing, which targets its promotional efforts directly to the end users; however, detailing is similar to other forms of promotion, used in traditional markets, in a sense that it is both a marketing tool and an informational source (Nelson, 1974).

The detailing efforts have been losing its impact over the years due to significant changes in the selling. The primary change is from managed care organizations' growing influence in regulating the use of drugs coupled with an increasing number of physicians seeking more

objective scientific evidence of benefits (Robinson, 2001). Moreover, a more competitive detailing environment (LeadDiscovery, 2006); lack of new blockbuster drugs to gain physicians' attention (PricewaterhouseCoopers, 2008); and the increasing role of direct-to-consumer advertisements and electronic detailing (Davidson and Sivadas, 2004) all have contributed to the declining detailing impact. In fact, the average detailing duration dropped from five minutes in 1998 to less than one minute in 2004 (Yi, 2008), signaling the physicians' declining interest in hearing from the reps.

Many researchers have found evidence of high market share of detailing voice positively impacting the market share of detailing product (Jones, 1990; Shimp, 2000; Gonul, Carter, Petrova, and Srinivasan, 2001; Pesse, Erat, and Erat, 2006). As a result, pharmaceutical firms are committed to maximizing their share of voice within their resource constraint in an effort to increase sales; one way to increase the share of voice without adding more sales reps is to detail multiple products instead of single product.

2.1. Share of Voice Computation

To derive the share of detailing voice, physician detailing equivalent (PDE) weights for the product and the market are computed first; PDE is used by the industry to calculate total detailing efforts when detailing is done in multiple sequences, and the PDE weights reflect the relative detailing impact of each sequence. Equation (1) shows how PDE_{jkl}, which denotes physician detailing equivalent for physician j, in time period k, for product l, is calculated:

$$PDE_{jkl} = \sum_i (W_i \times D_{ijkl}) \quad for \ \forall \ i, j, k, l \quad (1)$$

D_{ijkl} is defined as the total number of details made in sequence i to physician j in time period k, for product l, while W_i defines the PDE weight for detailing sequence i. In addition, the weights play an instrumental role in computing share of voice in time period k, for product l, denoted as SOV_{kl}, as shown in Eq. (2):

$$SOV_{kl} = \frac{\sum_j PDE_{jkl}}{\sum_l \sum_j PDE_{jkl}} \quad \text{for } \forall k \quad (2)$$

2.2. Impact of Detailing Multiple Products to Share of Voice

The traditional PDE weights, shown in Table 1, are provided by the firm sponsoring this research; the table shows that the full weight of one is assigned to the first detailing product independent of the number of products in the detailing portfolio. In other words, as long as the product is detailed in the first position, it will always carry the full detailing weight. Similarly, if the product is detailed in the second sequence,

it will always have the PDE weight of 0.6. Finally, any product detailed in the third sequence or beyond will have the PDE weight of 0.3. Clearly, the firms detailing multiple products will have higher share of voice with 1.9 PDE when a sales rep details three products to a physician in a single visit versus 1 PDE when a rep details a single product.

According to the sponsoring firm, the origination of the PDE weights is based on primary market research to physicians. Interviews with sales operations professionals in other companies made possible by pre-existing professional contacts have validated that these values are similar across the industry.

TABLE 1: SUMMARY OF TRADITIONALLY APPLIED PDE WEIGHTS FOR DETAILING SEQUENCE BASED ON THE NUMBER OF DETAILING PRODUCTS

	1st position	2nd position	3rd + position
In single product detailing	1.00	-	-
In two-product detailing	1.00	0.60	-
In three+ product detailing	1.00	0.60	0.30

2.3. Limitations of Traditional Approach

The traditional approach in utilizing PDE weights has two major limitations. The first limitation is that the approach always gives benefit to detailing more products versus detailing fewer products by a way of increasing SOV. This is a flawed assumption because it is hard enough to access physicians in recent years and when the access is granted, they are not allowing for more time if reps detail more products with average details lasting less than a minute (Yi, 2008). More likely, the detailing products will likely cannibalize the individual detailing impact due to the spreading of information in a fixed time. Thus, always giving SOV advantage to multi-product detailing strategy may mislead management in making sound sales operations decisions.

Secondly, the PDE weight for each detailing sequence is constant for all physicians regardless of how well they respond to details. This is another flawed assumption because physicians and their patients' needs are different; if the firms do not accommodate for these differences and neglect to provide individualized detailing strategy, a significant negative consequence such as suboptimal resource allocation and undesirable sales force performances are likely consequences (Yi, Anandalingam, and Sorrell, 2003).

In spite of the significance of these weights have on sales operations decisions, surprisingly little is known about them via published research. In this paper, we propose a new approach to minimize the impact of the aforementioned limitations to sales performance, and investigate the feasibility and performance of

the approach when implemented to a small sample of physicians.

III. DATA

A pharmaceutical company with annual US sales over \$2 billion sponsored this research on the condition that the company would receive the model and report of the findings while remaining anonymous and having a say in when to release the research publication. The firm provided (1) the detailing history and respective sales data for one of its territories in the Northeast region, comprising a total of 72 physicians on its target list, and (2) team of domain experts and their time to help in this research on a \$275 million prescription drug product. This drug was launched in late 1990s, is promoted by multiple sales forces in different detailing sequences, and competes against four branded products for market share. The product was selected for this research mainly due to the wealth of detailing data available.

Pharmaceutical companies generally target physicians detail based on the volume of prescriptions they generated in both the drug class and the drug itself. The physicians were sorted in order of prescription volume in the disease class, and then they were grouped into 10 equal segments, with the first decile representing the lowest prescribers and the 10th decile the highest; the higher-decile physicians received more detailing visits from the sales reps than did the lower-decile physicians.

To initiate this study and find the direction of the research, we merged two sets of data, by physician identification number, to form the database. One data set contains the number of prescriptions that the physicians on the company's target list wrote for the studied drug and its competitors. The second contains information about the sales reps' detailing activity with the physicians. Two years' worth of data, broken out into eight quarters from 1st quarter 2003 through 4th quarter 2004, were collected for the study; we used quarterly data because monthly data contained too much noise for the research.

In addition, the company provided the competitive sales activity data at the territory level for the same period as that used for the data analysis. It captured information on all competing products marketed in the same therapeutic area of the company's product: the competitors' sales force structure; the number of sales reps detailing the drugs; and the detailing sequences of the products for each territory. There were concerns about data integrity of other promotional events, such as direct-to-consumer advertising, electronic detailing, journal advertising, and sponsored medical educational programs; these data points were excluded from this study.

IV. NEW APPROACH: KNOWLEDGE-BASED APPROACH

A knowledge-based approach is defined as one designed to extract and integrate the tacit and explicit knowledge within the organization and then to apply it as a vital component in the quantitative modeling process to improve the organization's performance as well as gaining insights that can provide competitive advantage (Blattberg and Hoch, 1990). This paper proposes a knowledge-based approach at the physician level to explore whether or not limitations of the traditional approach can be alleviated while improving sales operations involving multiple products. The theoretical framework for this approach is founded on knowledge and micromarketing.

4.1. Theoretical Framework for Knowledge and Micromarketing

Knowledge is defined as the set of justified beliefs that enhance a firm's capability to take effective action (Nonaka, 1994). Knowledge can largely be divided into two areas: tacit and explicit. Tacit knowledge refers to insights, intuitions, and hunches that are not

easily verbalized or communicated. This tacit knowledge is critical in decision making process because it is the primary source of problem definition and alternatives (Davenport and Prusak, 1998). On the other hand, explicit knowledge refers to that which can be formally expressed and collected as data, words, and software, therefore, be easily diffused throughout an organization (Davenport and Prusak, 1998). Researchers have found that converting tacit knowledge into explicit knowledge and integrating the two significantly enhances a company's competitive position by improving organizational capability, competence, and performance (Brown and Duguid, 1998). Moreover, knowledge integration across different functions within a firm has demonstrated improvement in decision making quality and organizational performance (Blattberg and Hoch, 1990; Cai, 2006; Liebowitz, 2008).

Recent studies have shown that knowledge capture and management can be improved by integrating visualization into the modeling process, with visually agreed-upon knowledge being very successful in capturing and segmenting complex knowledge (Coffey, Hoffman, and Cañas, 2006; Strohmaier and Lindstaedt, 2007). Also, integrating domain experts' knowledge with secondary data that can be used to derive visually agreed-upon promotional response patterns has proven to be an effective way to identifying responsive physicians, leading to derivation of more accurate response functions and, consequently, improvement in the quality of the detailing plan (Yi et al., 2003). Moreover, it has been demonstrated that the promotional response function parameters for individual physicians can improve its accuracy by calibrating the parameters to reveal responsiveness as defined by the experts (Yi, 2008).
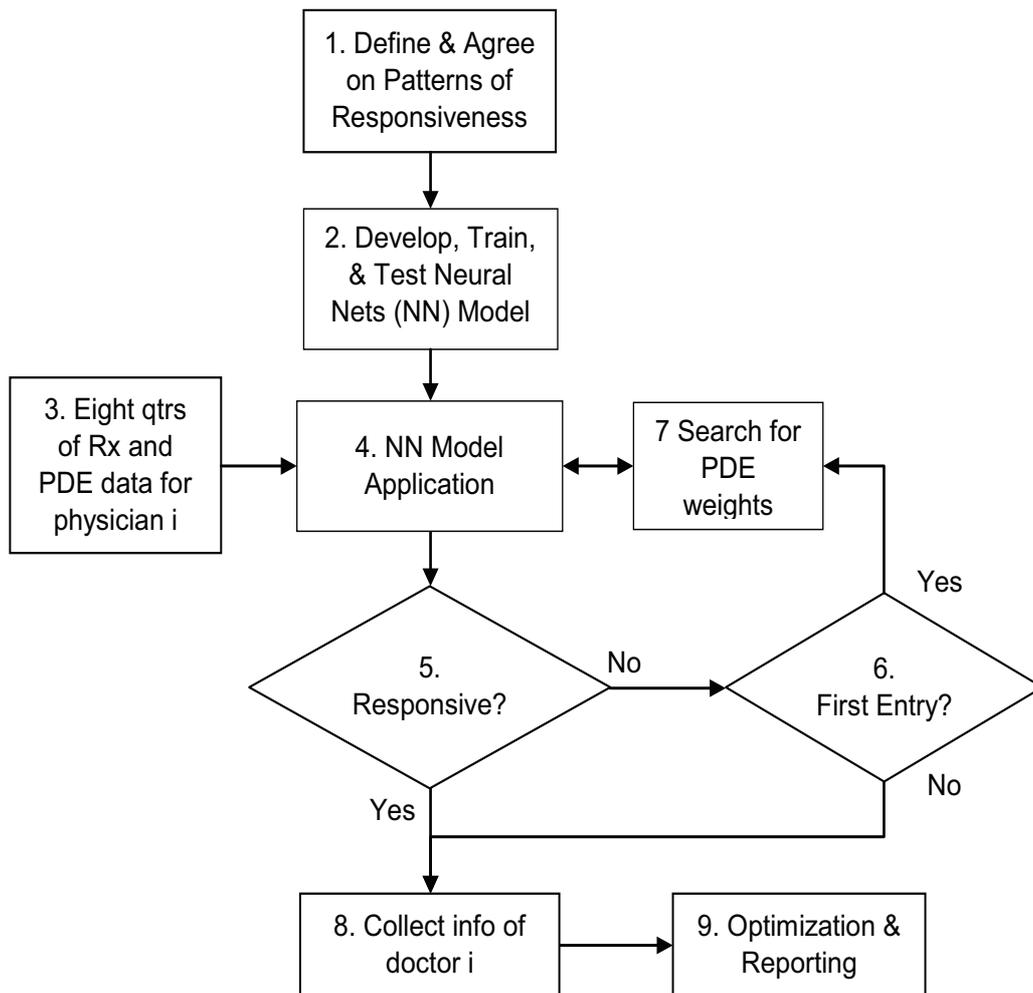
Based on these previous studies, this paper hypothesizes that optimally utilizing knowledge is critical to improvement of detailing planning. In addition, accurate PDE weights are those that visually reveal physicians' responsiveness by matching its pattern to the predetermined responsive patterns developed by domain experts, resulting in improved promotional functions and detailing plans. Moreover, since PDE weights are inputs to SOV computation as well as to detailing planning, improvement in the weights will also improve the qualities of SOV calculation as well as detailing planning. These benefits are expected to result in minimization of non-value-added costs, making the sales reps more effective and therefore increasing revenue.

Micromarketing is tailoring marketing plans at the consumer level to better accommodate individual differences in responses to promotions (Leeflang and Wittink, 2000; Zhang and Krishnamurthi, 2004). In addition, similar to traditional consumers, physicians respond better to marketing messages tailored to their individual needs (Yi, 2008). Therefore, incorporating micromarketing as part of a knowledge-based approach is expected to be more effective than the traditionally targeting physicians at a macro level, and further increase the effectiveness of sales operations.
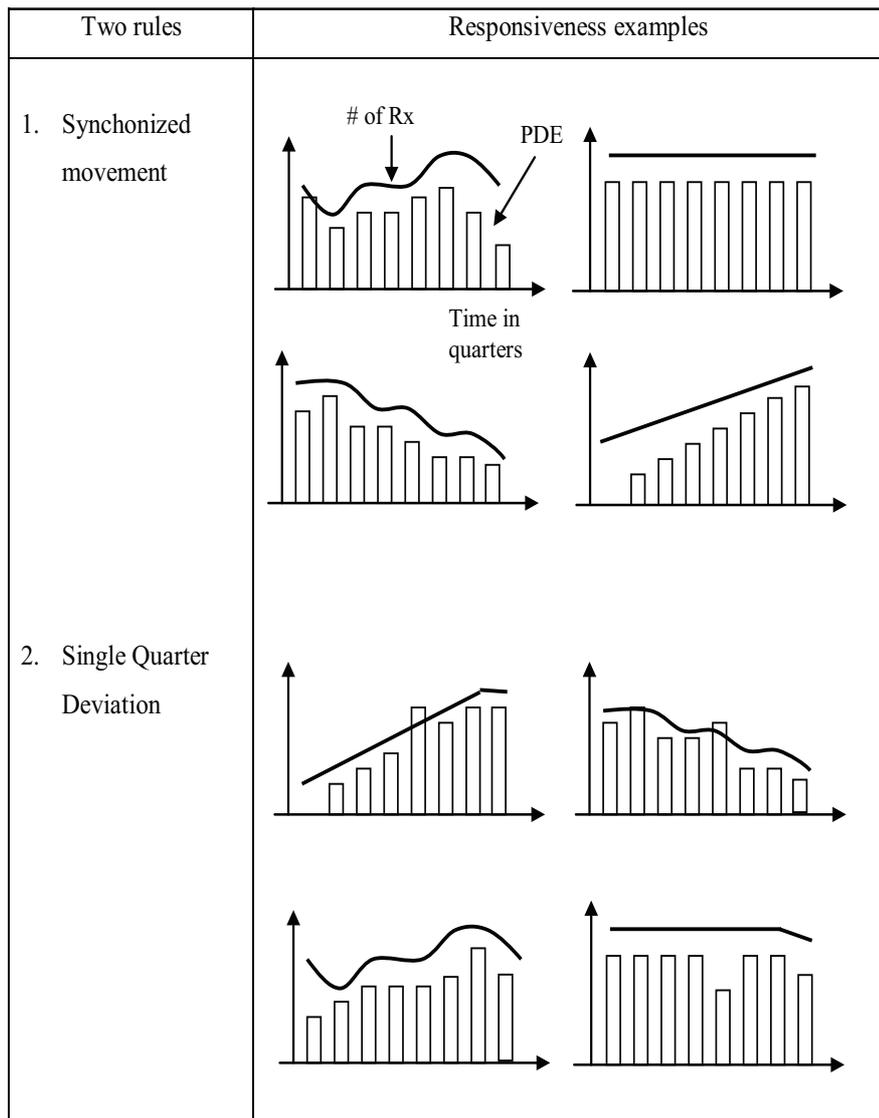
4.2. Process Flow of the Knowledge-Based Approach

The process flow of this approach is shown in Figure 1. This flow is developed to provide transparency to the proposed process.

```
                    ┌─────────────────┐
                    │ 1. Define & Agree│
                    │  on Patterns of  │
                    │  Responsiveness  │
                    └─────────────────┘
                             │
                             ▼
                    ┌─────────────────┐
                    │ 2. Develop, Train│
                    │  & Test Neural   │
                    │  Nets (NN) Model │
                    └─────────────────┘
                             │
  ┌──────────────┐           ▼           ┌──────────────┐
  │ 3. Eight qtrs│   ┌──────────────┐    │ 7 Search for │
  │  of Rx and   │──▶│ 4. NN Model  │◀──▶│     PDE      │
  │  PDE data for│   │  Application │    │   weights    │
  │  physician i │   └──────────────┘    └──────────────┘
  └──────────────┘           │                   ▲
                             ▼            Yes     │
              ┌────────────┐     No   ┌────────────┐
              │    5.      │─────────▶│    6.      │
              │Responsive? │          │First Entry?│
              └────────────┘          └────────────┘
                    │  Yes                  No │
                    ▼                          │
           ┌──────────────┐        ┌──────────────────┐
           │ 8. Collect   │───────▶│ 9. Optimization &│
           │ info of      │        │    Reporting     │
           │ doctor i     │        └──────────────────┘
           └──────────────┘
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FIGURE 1: PROCESS FLOW OF THE KNOWLEDGE-BASED APPROACH

In Step 1, the definition of responsiveness, based on the visual relationship between PDE and prescription volume over time, is constructed by working with a cross-functional team that includes representatives from Sales Operations, Sales, Marketing, Market Research, and Information Management. Each team member carries a title of manager or higher and at least three years of work experience in this brand as well as familiarity with the territories selected for the research. This cross functional team defined responsiveness based on two sets of rules and those not meeting these rules are defaulted as non-responsive. The two rules of responsiveness are: 1) synchronize movement for all eight quarters, and 2) allowing for a single quarter deviation from the synchronize movement property. Figure 2 illustrates examples of responsiveness based on these two rules.

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Two rules	Responsiveness examples
1. Synchonized movement	
2. Single Quarter Deviation	

FIGURE 2: EXAMPLES OF PREDETERMINED PATTERNS OF PHYSICIAN RESPONSIVENESS TO DETAIL

The non-responsiveness examples, defaulted from not meeting the aforementioned rules, demonstrate cases where there exists no or insufficient visible pattern of relationship between PDE and prescription volume over time and are shown in Figure 3. Clearly, detailing alone cannot explain these physicians prescribing behavior.
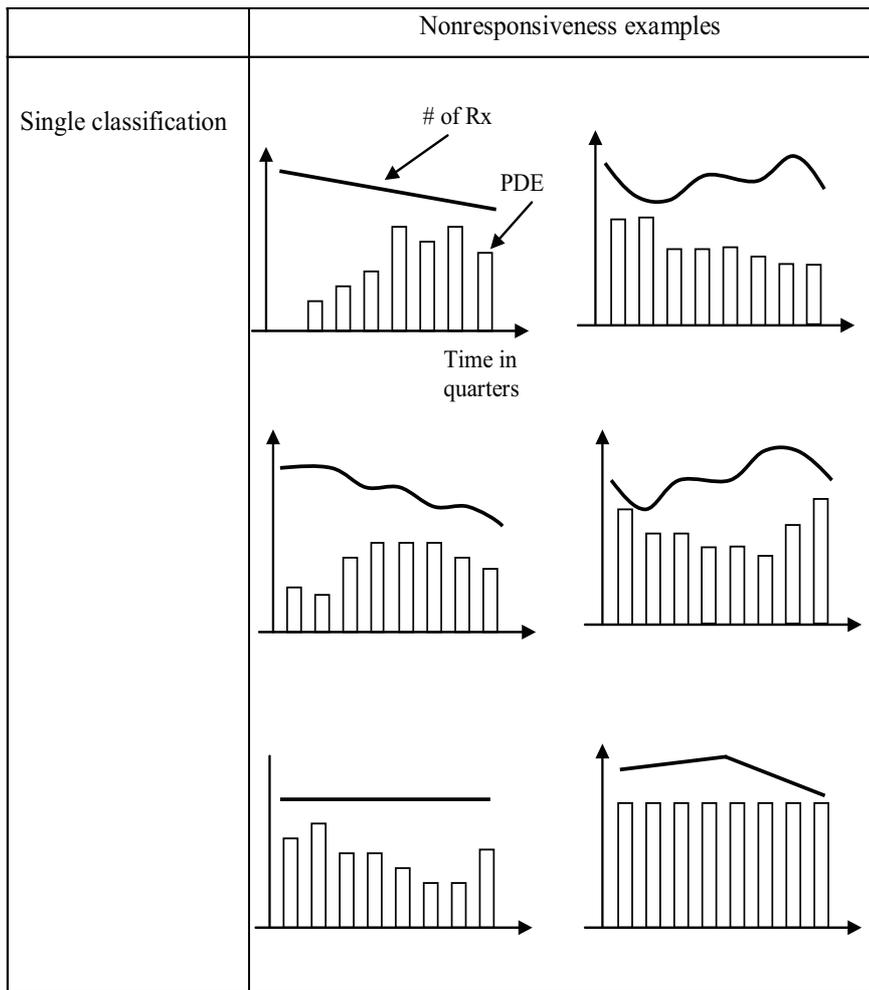
FIGURE 3: EXAMPLES OF PREDETERMINED PATTERNS OF PHYSICIAN NONRESPONSIVENESS TO DETAIL

In Step 2, a neural network (NN) model is developed to identify, from the target physician pool, individual physicians who are responsive to details. The main reason for using NN model in this study is because it automates otherwise manually intensive activity of classfying hundreds of physicians into two categories of responsiveness based on visual patterns between PDE and respective prescription volume for eight quarters developed in Step 1. In addition, strengths of NN models are the properties of adaptability, nonlinearity, fault tolerance, and input-output mapping (Jain and Vemuri, 1999; Kim, Lee, and Aguihotri, 1995). On the other hand, NN's limitations are that its functionality is often perceived as black box, the model-development process is more art than science, and time consuming data-preparation step. (Livingstone, Manallack, and Tetko, 1997).

Similar to the work done by Yi et al. (2003), this research uses a back-propagation network with 16 input nodes (8 quarters of PDE and 8 quarters of the respective prescription volume (TRx), 1 hidden layer containing 7 neurons, and 1 binary output node (1 for responsive and 0 for nonresponsive physicians). The model was developed with 450 training samples with known results. With a predicted accuracy of 84%, the NN model compared favorably with the logistic regression model that produced a predicted accuracy of 53%, using Eq. (3).

$$\text{Predicted accuracy } \% = \left[1 - \frac{\sum_{i=1}^{n} Abs(Act_i - Pred_i)}{n} \right] 100\% \qquad (3)$$

where

    Act_i actual output of physician i
    $Pred_i$ predicted value for physician i
    Abs absolute value function
    n number of testing samples

In Step 3, the eight quarters of TRx and respective PDE data for physicians are prepared for Step 4, the NN model application. In Step 5, responsiveness of physicians is determined, with nonresponsive physicians' data directed to Step 6 and responsive physicians' data to Step 8.

All nonresponsive physicians entering Step 6 for the first time go through to Step 7, where a nonlinear mathematical model interface with the NN model searches for a set of PDE weights that reveal physicians' responsiveness to detailing efforts; the nonlinear program interfacing with the NN model is shown here:

Maximize $NN(Rx_{jk}, PDE_{jk})$ for $k \quad 1,...,8$ (4)

$s.t.$

$$PDE_{jk} \quad \sum_{i=1}^{3} (W_{ij} \quad D_{ijk}) \text{ for } k \quad 1,...,8 \qquad (5)$$

$W_{ij} \leq 1$ for $\forall i$ (6)

$W_{ij} \geq W_{i+1,j}$ for $i \quad 1,2$ (7)

all variables ≥ 0 (8)
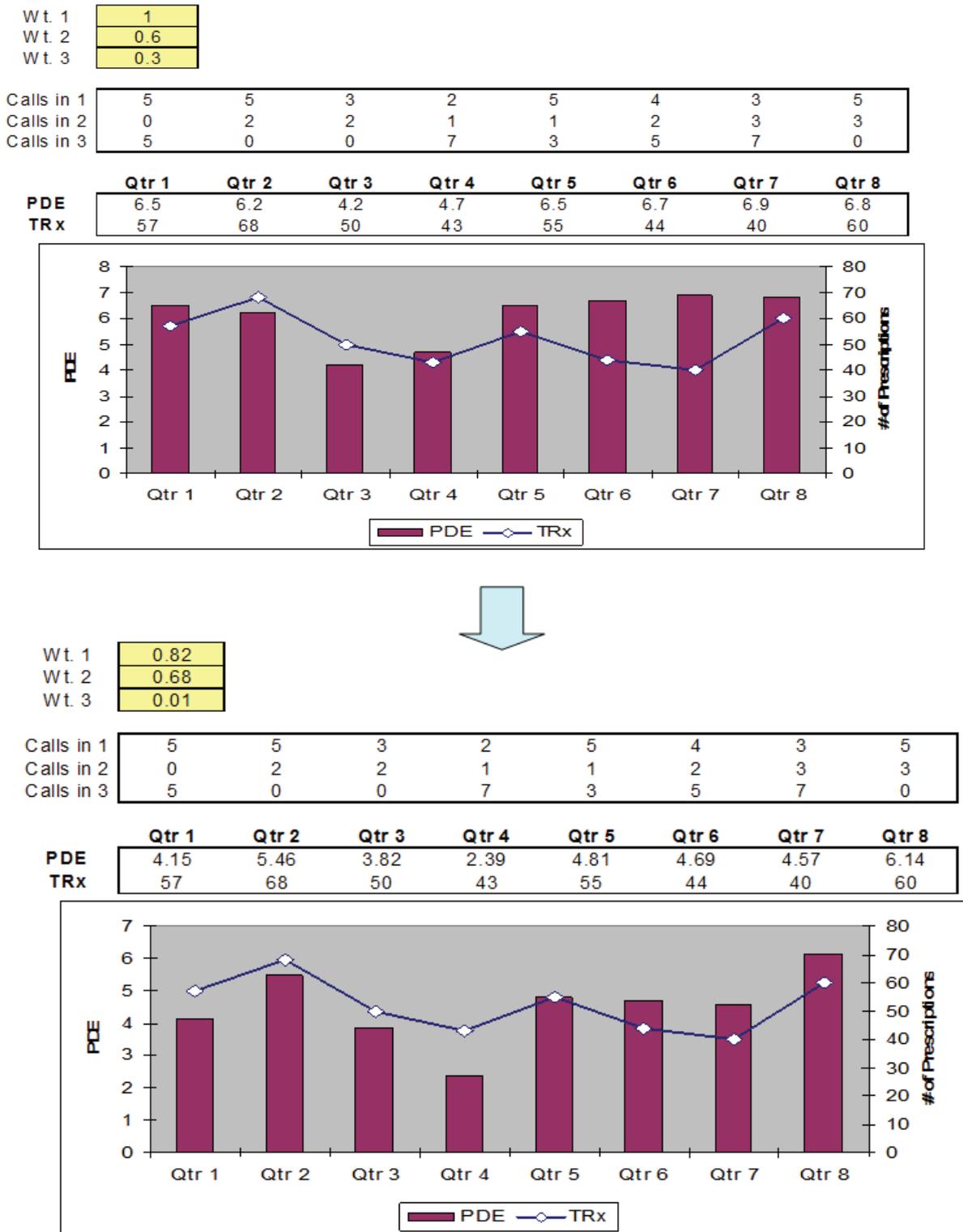
Where $NN(Rx_{jk}, PDE_{jk})$ are trained neural network function, returning 1 if physician j is responsive and 0 if physician j is nonresponsive based on relationship between Rx written and PDE over eight quarters; PDE_{jk} is the physician detail equivalent for physician j in quarter k; Rx_{jk} is the total number of prescriptions written by physician j in quarter k; W_{ij} is the detailing weight for the i^{th} sequence for physician j; D_{ijk} is the total number of details made from the i^{th} sequence to physician j in quarter k.

The objective function, given by (4), maximizes the number of responsive physicians in the first summation while maximizing the summation of the weights in the second summation. The first summation interfaces with the trained NN model by providing, to the model, the physician-level prescription data and the PDE data for all eight quarters, given by Rx_{jk} and PDE_{jk}, respectively, to determine the responsiveness of the targeted physicians.

The first constraint, given by (5), defines PDE for each physician in each quarter. The set of PDE weights, for the i^{th} position to physician j, W_{ij}, is initialized to 1, 0.6, and 0.3 for detailing positions 1, 2, and 3+, respectively. Constraint (6) sets the upper limit for the weight to be one. Constraint (7) forces the weights of preceding detailing positions to be bigger than the subsequent ones to reflect the inverse relationship between the detailing time and the order in which a product is detailed as well as to limit the searching space for the nonlinear program. The last constraint, given by (8), defines the non-negativity condition for all variables. Figure 4 illustrates how this step works by having a physician visually fitting to the nonresponsive definition with the traditional set of PDE weights, but the optimization algorithm found a new set of PDE weights to make the physician fit the definition of responsiveness, and this new set of weights replaces the traditional weights for this physician, with the physician classified as responsive.

Wt. 1	1
Wt. 2	0.6
Wt. 3	0.3

Calls in 1	5	5	3	2	5	4	3	5
Calls in 2	0	2	2	1	1	2	3	3
Calls in 3	5	0	0	7	3	5	7	0

	Qtr 1	Qtr 2	Qtr 3	Qtr 4	Qtr 5	Qtr 6	Qtr 7	Qtr 8
PDE	6.5	6.2	4.2	4.7	6.5	6.7	6.9	6.8
TRx	57	68	50	43	55	44	40	60

Wt. 1	0.82
Wt. 2	0.68
Wt. 3	0.01

Calls in 1	5	5	3	2	5	4	3	5
Calls in 2	0	2	2	1	1	2	3	3
Calls in 3	5	0	0	7	3	5	7	0

	Qtr 1	Qtr 2	Qtr 3	Qtr 4	Qtr 5	Qtr 6	Qtr 7	Qtr 8
PDE	4.15	5.46	3.82	2.39	4.81	4.69	4.57	6.14
TRx	57	68	50	43	55	44	40	60

FIGURE 4: AN EXAMPLE OF DERIVING A SET OF NEW PDE WEIGHTS FOR AN ACTUAL PHYSICIAN WHO APPEARED VISUALLY NONRESPONSIVE WITH THE TRADITIONAL SET OF PDE WEIGHTS.

In Step 8, information on each physician's responsiveness and the set of respective PDE weights for each of them is collected and stored. For the nonresponsive physicians, PDE is determined by taking the average PDE weights from the responsive physicians for each detailing sequence.

In Step 9, physician responsiveness and PDE weights are merged with physician data and the company's resource data to formulate a nonlinear programming model. The objective of this model is to determine the optimal plan for detailing the firm's target physicians to maximize quarterly profit. This formulation is shown here:

$$\text{Maximize} \quad \sum_i [\text{PRF}_i(PDE_i) \cdot \text{Price} - \text{Cost}_i(PDE_i / \text{E})]$$

$$+ \sum_{d=1}^{10} [\text{TP}_d * \text{PRF}_d(PDE_d) \cdot \text{Price} - \text{Cost}_d(PDE_d/\text{E})], i \in I \tag{9}$$

s.t.

$$PDE_i \geq \sum_{j=1}^{3} W_{ij} \cdot D_{ij}, \text{ for all } i \tag{10}$$

$$\overline{W_j} \geq \sum_{i=1}^{n_j} W_{ij} / n_j, \text{ for } j = 1, 2, 3 \tag{11}$$

$$PDE_d \geq \sum_{j=1}^{3} \overline{W_j} \cdot TD_{id}, \text{ for all } d \tag{12}$$

$$\sum_{j=1}^{n_j} \sum_{i=1} (W_{ij} \cdot D_{ij}) + \sum_{j=1}^{10} \sum_{d=1} (\overline{W_j} \cdot TD_{id}) \leq \text{R}_j, j = 1, 2, 3 \tag{13}$$

all variables ≥ 0 (14)

where

$PRF_i(x)$ promotional response function for physician or decile i, returning expected prescription volume for x detail in a quarter

PDE_i physician detail equivalent for responsive physician or decile i

R_j total quarterly resource for the jth position details

W_{ij} detailing weight for responsive physician i for detailing position j

D_{ij} total details that need to be made in the ith position to responsive physician j

TD_{id} total details that need to be made in the i^{th} position to nonresponsive physician in decile d

TP_d total physicians in decile d

Price   price of a single prescription of the drug

Cost_i cost to detailing physician i

E   efficiency factor to account for empty efforts directed to the physicians' offices

n_j number of responsive physicians for detailing sequence j

The objective function, given by (9), maximizes the quarterly profit from the sales force efforts. The first summation in the function calculates the optimal detailing plan to generate maximum profit from the physicians who are responsive to the sales force's detailing efforts:

the promotional response function of PDE_i details to physician i, given by $PRF_i(PDE_i)$, produces the number of prescriptions written by physician i; this is then multiplied by the price per prescription, price, to arrive at revenue; the cost to detailing physician i is given by cost(PDE_i/E), where E, which denotes efficiency factor and is less than one, accounts for the empty efforts made by the sales reps; and taking the difference between the revenue and cost per physician i and summing up the profit for all the responsive physicians gives the total profit generated by this group.

The second summation in the function calculates the profit from the nonresponsive physicians: since there is no visually discernable response pattern, the promotional response function to detailing effort PDE_d, given by $PRF_d(PDE_d)$, is derived at decile level d based on average PDE weights from the responsive physicians; this function produces the average number of prescriptions written by an average physician from decile d; multiplying the number of prescriptions by price and subtracting the cost associated with the detailing effort, again including E, gives the profit per physician from decile d; and summing for all the deciles gives the total profit generated from this group.

Constraint (10) defines PDE for physician i, based on the PDE weights found specifically for responsive physician i in detailing position j derived earlier, in Step 7. The set of weights provides the visually recognizable pattern of responsiveness for physician i, which enables the program to locate the optimal set of details for that physician.

The average PDE weights for responsive physicians defined for each detailing sequence is in constraint (11). Constraint (12) defines PDE for the nonresponsive physicians per decile d. Constraint (13) sets the upper limit R_j on the total quarterly detailing resources for the drug for each sequence j, while the non-negativity condition is set by constraint (14).

V. APPLICATION AND RESULTS

To measure the effectiveness of the knowledge-based approach, the sponsoring firm allowed its implementation in a randomly selected territory where the research data were collected; this territory, located in the Northeast region with 72 target physicians, are called the test group. The implementation period is from March 2005 through June 2005, with the March used as a grace period to correctly implement the plan. The result from the latter three months, or the second quarter of 2005, is used to measure the performance of the test group and compare it against a control group. This control group selected is also from the Northeast region and the prior sales performance and target physician size were both within ±5% of the test group.

The detailing plan with traditional PDE weights of [1, 0.6, 0.3] is calculated to an SOV of 15%, which is what management wanted for this product. In addition, running the NN model with the traditional weights results in identifying 19 physicians, or 26% of the total 72 physicians, as responsive to details based on domain experts' definition of responsiveness.

The knowledge-based approach finds that, on average, when there is only one product to be detailed, the PDE weight indeed remains one. However, with a product detailed in two positions, the first and second positions carry average weights of 0.82 and 0.68, respectively. With a product detailed in three positions, the weights of the first, second, and subsequent positions are 0.70, 0.41, and 0.02, respectively. Table 2 below summarizes the average PDE weights in relation to the size of detailing products and the detailing sequence.

TABLE 2: THE AVERAGE PDE WEIGHTS DERIVED USING THE KNOWLEDGE-BASED APPROACH FOR RESPONSIVE PHYSICIANS BASED ON THE NUMBER OF DETAILING PRODUCTS

	1^{st} position	2^{nd} position	3^{rd} + position
In single product detailing	1.00	-	-
In two-product detailing	0.82	0.68	-
In three+ product detailing	0.70	0.41	0.02

The derived PDE weights for individual physicians matched 32 physicians as responsive to detailing efforts over eight quarters, as oppose to 19 physicians based on the traditional approach. This is 44% of the total physicians in the sample, which is approximately 71% increase from the number found using the traditional weights.

In computing SOV, when the new PDE weights are applied to the traditional detailing plan, it resulted in SOV of only 9%, which is significantly lower than 14% SOV that the management wanted and thought they were getting for this product. It is due to this discrepancy in perceived SOV and actual SOV, the sponsoring firm had been operating at a strategic disadvantage against its competitors and not surprisingly has trouble meeting the sales forecast for the last two years.

The optimization of sales resources based on the derived PDE weights recommends a different sequencing of the product, with strong emphasis on the primary and secondary details while virtually eliminating the need to detail in the other sequence. The detailing plan based on the new approach results in SOV of 13% with the same amount of sales force resource; this is a lot closer to the target SOV set at 14% by the management for this product.

The knowledge-based approach requires 11% more PDEs for the responsive physicians and 6% fewer for their nonresponsive counterparts. After three months of implementation of this approach, the test group's profit increased by more than 9% compared to the control group. Also, sales reps from the test groups had, on average, 29% more detailing time per PDE, further attesting to the quality of detailing plan of the proposed approach. These findings are summarized in Table 3.

TABLE 3: PERFORMANCE COMPARISON SUMMARY BETWEEN TRADITIONAL AND KNOWLEDGE-BASED APPROACHES

	% of responsive physician	SOV	Detailing duration	Profit
Traditional Approach	26%	9%	-	-
Knowledge-based Approach	44%	13%	+29%	+9%

VI. CONCLUSION

The knowledge-based approach presented in this paper revealed that the first detailing sequence does not carry the full weight in multiple product detailing situations. What we found, however, is that as the number of products in the detailing portfolio increases, each detailing sequence carries less weight, possibly due to the products cannibalizing each other's time and information. Furthermore, products that are detailed in the 3rd position or later add no benefit to sales operation, and therefore limit the size of the detailing portfolio to two products.

This study also validates the significance of using a micromarketing strategy in the pharmaceutical industry to gain competitive edge and improve customer relationships by understanding their needs better. In fact, by planning at the physician level, it was revealed that 44% of physicians are responsive to details, as opposed to 26% of physicians when viewed in a macro level. Lastly, the new PDE weights derived at the physician level provided an improved detailing plan that has increased SOV from 9% to 13%, resulting in improved profit of 9% when the test group is compared to the control group.

Some limitations of this research include the sample size being relatively small with 72 physicians when total number of physicians prescribing this product exceeds 10,000; the determination of responsive and nonresponsive behaviors is based on one cross-functional team's best judgment; and the responsiveness is measured strictly based on the relationship between physician details and the physicians' respective prescribing patterns, while omitting the other promotional data due to the data-integrity issue, leaving some prescribing behaviors unexplained.

To improve this research, the physician sample size needs to be increased from 72 physicians and cover more than just a single territory to improve overall confidence in the data and ultimately study result. Other areas of research extensions are increasing the test duration in comparing the sales performance between the test and control groups to reduce errors; incorporating other promotional data as part of the study to better explain physicians prescribing behaviors; and revisiting the responsiveness definitions to make it more robust.

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