# ANALYTICAL INTEGRATION AND DATA-DRIVEN DECISION MAKING IN COMPLEMENTARY AND ALTERNATIVE MEDICINE

**Kessara Kanchanapoom**

**A Dissertation Submitted in Partial**
**Fulfillment of the Requirements for the Degree of**
**Doctor of Philosophy (Business Administration)**
**School of Business Administration**
**National Institute of Development Administration**
**2019**

**ANALYTICAL INTEGRATION AND DATA-DRIVEN DECISION MAKING IN COMPLEMENTARY AND ALTERNATIVE MEDICINE**

**Kessara Kanchanapoom**

**School of Business Administration**

---

Associate Professor.................................................................Major Advisor

(Jongsawas Chongwatpol, Ph.D.)

The Examining Committee Approved This Dissertation Submitted in Partial Fulfillment of the Requirements for the Degree of Doctor of Philosophy (Business Administration).

Assistant Professor.................................................................Committee Chairperson

(Piya Ngamcharoenmongkol, Ph.D.)

Associate Professor.................................................................Committee

(Jongsawas Chongwatpol, Ph.D.)

Assistant Professor.................................................................Committee

(Saranath Lawpoolsri Niyom, Ph.D.)

Associate Professor.................................................................Dean

(Tatchawan Kanitpong, Ph.D.)

April 2020

# ABSTRACT

| | |
|---|---|
| **Title of Dissertation** | Analytical Integration and Data-Driven Decision Making in Complementary and Alternative Medicine |
| **Author** | Miss Kessara Kanchanapoom |
| **Degree** | Doctor of Philosophy (Business Administration) |
| **Year** | 2019 |

---

Customer Lifetime Value (CLV) measures the success of an organization by estimating the net value its customers contribute to the business over the lifetime of the relationship. How can organizations assess their customers' lifetime value and offer strategies to retain those prospects and profitable customers? The first part of this dissertation offers an integrated view of methods to calculate CLV considering scenarios ranging from finite-and-infinite customer lifetimes to customer migration and Monte Carlo simulation models.

In addition to the CLV models, customer segmentation is considered the fundamental marketing activity assisting enterprises to gain a deeper understanding of their customers' characteristics and needs and, consequently, develop appropriate strategies to strengthen the relationship between them and their customers. Many segmentation models proposed in the literature have been based on specific criteria or attributes such as psychology, demography, or behaviors. At present, the recency (R), frequency (F), and monetary values (M) and cluster analysis models are two popular methods used to create data-driven behavioral segmentation. One of the limitations of those two methods is that most studies focus on transaction-based data, that is, past customer behavior. Therefore, the second part of this dissertation presents a case for integrating CLV and the probability of customer migration, also called the probability that a customer will return in the future, in the segmentation models. The first scenario uses a slightly modified RFM model, replacing the monetary value (M) with

CLV. The second scenario integrates recency, frequency, CLV, length of relationship (L), and the probability of migration in the k-means clustering technique.

Both CLV, cluster analysis, and RFM models are validated in the context of the healthcare industry, particularly in the area of complementary and alternative medicine (CAM), which refers to practices for people or patients who seek alternative treatment or illness prevention along with or instead of conventional medicines. The results show that understanding CLV and improving customer segmentation models can help the organization develop strategies to retain valuable customers while maintaining profit margins.

In addition, Appendix A illustrates a teaching case study on the application of business intelligence and marketing analytics to making proper decisions in a competitor-oriented pricing environment in Complementary and Alternative Medicine (CAM) Industry. This case study helps conceptualize the nature of the complementary and alternative medicine (CAM) Industry, understand the concept, pros, and cons of price wars, outline what factors/criteria are needed to get more insights about customers, utilize the RFM model and cluster analysis to segment customers based on their similar characteristics, illustrate how to calculate customer lifetime value (CLV), utilize the business intelligence framework to justify the decision choices, and finally, understand how to make decisions in competition-oriented pricing situations.

# ACKNOWLEDGEMENTS

My sincere appreciation goes to everyone on my dissertation. Firstly, I would like to thank Associate Professor Dr.Jongsawas Chongwatpol, my advisor, for the supervision of my doctoral dissertation. I am so grateful to have a chance to get insightful comments, support, understanding, expert guidance, advice, and encouragement during a very difficult time of conducting doctoral dissertation. Under his guidance, I have developed a lot skills, especially in business analytics and been allowed to pursue my interests without any restrictions.

I would like to thank, Assistant Professor Dr.Piya Ngamcharoenmongkol for being my committee and chairman.

I would like to thank, Assistant Professor Dr. Sarath Lawpoolsri Niyom for being my committee.

I would like to thank Mr.Yuranan Pamornmontri, President of Panacee medical center, and his officers for providing the data used to perform the analysis and experiments in this dissertation.

Special thanks go to Miss Pojjamarn Keattitorn for her help in accessing to the sources of information and data. Thanks to ML.Nipada Devakul and Miss Kasarin Unnhasut for their encouragement.

I am also grateful to my colleague and friend, Mr.Kittiphod Charoontham, who has created a great supportive atmosphere and good comments.

Finally, I would like to thank my parents and my brothers - Associate Professor Dr. Tripetch Kanchanapoom and Dr.Termkiat Kanchanapoom (TK) for their love and support during all these difficult years. The pursuit of doctoral degree will not occur without encouragement and financial support from TK. Their support and encouragement is what allows me to be here today.

Kessara Kanchanapoom

April 2020

# TABLE OF CONTENTS

# LIST OF TABLES

# LIST OF FIGURES

**Figures** **Page**

# ABBREVIATIONS

| Abbreviations | Equivalence |
|---|---|
| CAM | Complementary and Alternative Medicine |
| CLV | Customer Lifetime Value |
| CRM | Customer Relationship Management |
| LRFMM | Length, Recency, Frequency, Monetary and Migration |
| RFM | Recency, Frequency and Monetary |

# CHAPTER 1

# INTRODUCTION

## 1.1 Research Background

Many organizations continually look for ways not only to know more about their customers' perspectives and behaviors, but also to maintain outstanding relationships with them. To handle this challenge, a key performance indicator that helps organizations select and target either their potential or profitable customers is customer lifetime value (CLV) (Ryals, 2002; Wilcox & Gurau, 2003). CLV measures the impact and outcome of the organization's CRM strategies and tactics in order to understand the effect their marketing activities have on their customers and how much profit their customers can generate for the organization (Wyner, 1996). These organizations need to understand what types of customers are likely to respond to the products or services offered and what types of customers are the most profitable for the organization. Customers are not equally profitable, do not require similarly dedicated resources, and are not the same even when they are receiving an identical product or service (Chang, Chang, & Li, 2012). Additionally, different customer segments may exhibit different patterns of attrition, switching, and reactivation. Thus, estimating the net value customers contribute to the business over their entire lifetime is essential to measuring the success or health of the organization.

However, CLV varies based on customers' purchasing behaviors, and the methods to estimate customer valuation can be substantially different across industries. How can organizations assess their customers' lifetime value and offer relevant strategies to retain prospective and profitable customers? Especially, it is often observed that these customers are, on one extreme, willing to switch from one vendor to another based on the products, services, and associated campaigns they receive or, on the other extreme, loyal to only one vendor based on their past experiences, satisfaction, or high switching costs. The first part of this dissertation seeks to answer this question and offers an integrated view of different methods for calculating customer lifetime values for both loyalty members and non-membership customers, who rarely participate in the loyalty program. The eleven CLV methods presented in this dissertation consider various scenarios from both finite and infinite customer-lifetime spans to customer migration and Monte Carlo simulation models. These models are then validated in the context of the popular complementary and alternative medicine (CAM) industry, where people go to clinics for treatment and illness prevention either together with or instead of conventional medicines (Gammack & Morley, 2004; Lavretsky, 2009). Guidelines for how to apply each CLV model are presented along with an executive dashboard that integrates customer data not only to estimate CLV and other related key performance indicators, but also to differentiate the customers' needs for health programs and their purchasing patterns for making better marketing-related decisions.

Even though we demonstrate how our integrated CLV models can be applied to measure customer value in the CAM-related healthcare industry, the details of CLV calculations and the guidelines for CLV implementation can be applied to other business settings. For researchers, the integrated CLV models in this dissertation, which consider the discount rate, attrition rate, and growth rate for both contractual (finite) and non-contractual (infinite) horizons; the probability that customers may return in the future; and simulation-based lifetime estimation, provide an overview of the mathematical estimation of lifetime values depending on the nature of the customers and the business circumstances. Practitioners, on the other hand, can benefit from promoting pro-active marketing strategies and allocating the right resources to different groups of customers based on the customer purchasing behavior and CLV estimation.

Apart from CLV, Customer segmentation is considered the fundamental marketing activity assisting enterprises to gain a deeper understanding of their customers' characteristics and needs and, consequently, develop appropriate strategies to strengthen the relationship between them and their customers (Kotler & Armstrong, 2018; McCarty & Hastak, 2007). It is one of the core functions of customer relationship management, primarily involving understanding customer profitability, retaining profitable customers, and delivering the right messages to the right customers. Different customer segments exhibit different patterns of attrition, switching, and reactivation; thus, enterprises must dedicate their resources to those segments in ways that fit their preferences and purchasing behavior. Many segmentation models proposed in the literature have been based on specific criteria or attributes such as psychology, demography, or behaviors. At present, the recency (R), frequency (F), and monetary values (M) and cluster analysis models are two popular methods used to create data-driven behavioral segmentation. The RFM model is widely used because of its simplicity and applicability in analyzing and understanding customer behavior characteristics by focusing on the three transaction-based RFM attributes (Chen, Zhang, & Zhao, 2017; Miglautsch, 2000). Cluster analysis integrates traditional demographic attributes such as age, gender, income, and education level with RFM, and non-demographic and behavioral attributes such as customers' preferences, attitudes, and lifestyles; product specification; and marketing-related attributes (Ballestar, Grau-Carles, & Sainz, 2018; Ek Styven, Foster, & Wallstrom, 2017).

One of the limitations of those two methods is that most studies focus on transaction-based data, that is, past customer behavior. Therefore, some scholars have incorporated the future behavior of customers into the model (Berger & Nasr, 1998; Gupta & Lehmann, 2006; Kumar, Ramani, & Bohling, 2004; Safari, Safari, & Montazer, 2016); for instance, the monetary (M) parameter in the classical RFM model is replaced with the customer lifetime value (CLV), which looks at the future value of customers considering their lifetime span with the enterprise or including CLV as one of the factors in the cluster- based segmentation. Still, the lack of considering whether current customers are still loyal to the enterprise or are exhibiting a pattern of likely attrition or switching to a competitor is a big concern in segmenting customers for further strategic and personalized campaigns.

How can organizations integrate their customers' lifetime value and the probability that their customers will likely return in the future as parts of RFM and cluster analysis to improve marketing decisions, especially in tailoring their products and services to match the customers' purchasing patterns? The second part of this dissertation seeks to fill the gap shown in Figure 1.1 and present a case for integrating

CLV and the probability of customer migration, also called the probability that a customer will return in the future, in the segmentation models. The first scenario uses a slightly modified RFM model, replacing the monetary value (M) with CLV. The second scenario integrates recency, frequency, CLV, length of relationship (L), and the probability of migration in the k-means clustering technique. Both models are validated in the context of the healthcare industry, particularly in the area of complementary and alternative medicine (CAM), which refers to practices for people or patients who seek alternative treatment or illness prevention along with or instead of conventional medicines (Gammack & Morley, 2004). Even though we present our model in the context of the CAM-related healthcare industry, the proposed segmentation models are applicable to any business setting. Researchers can learn the concept of CLV and customer migration and how these two future-driven aspects of customer loyalty can be used as core factors in the segmentation models, and practitioners can benefit by moving from using only historical, transaction-based data to integrating customer valuation and the probability that customers will stay with the enterprise in order to better understand the behavior of their loyalty customers. In doing so, enterprises can offer appropriate marketing strategies or allocate the right resources to the right groups of customers.

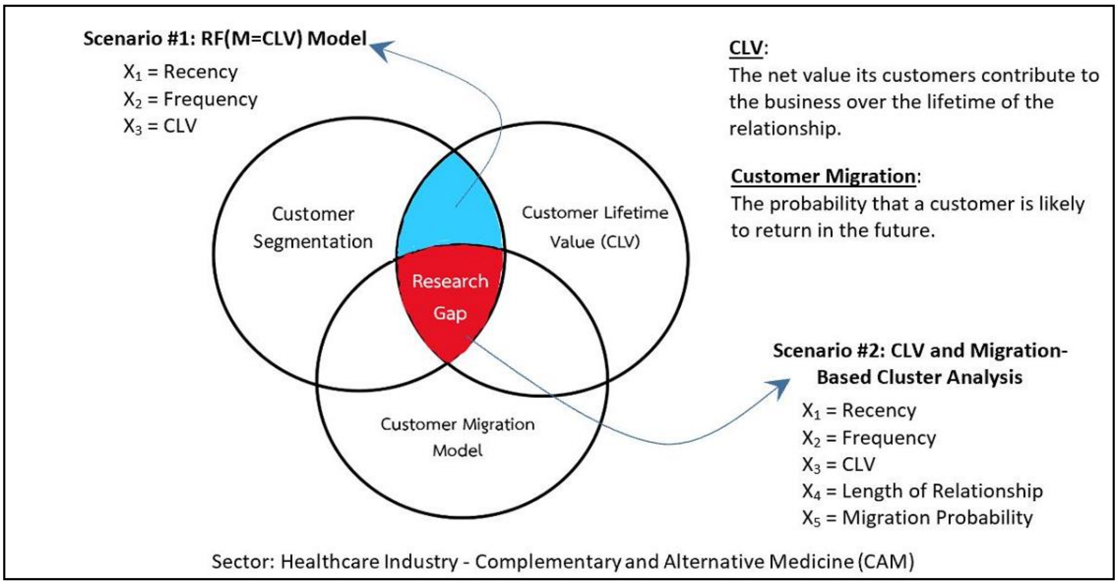



**Figure 1.1** Research Gap

The remainder of this dissertation is organized as follows. After a brief literature review on RFM, cluster analysis, CLV, and the customer migration model in chapter 2, Chapter 3 provides the details of the application of customer segmentation analysis in the Complementary and Alternative Medicine (CAM) industry along with the research framework of this dissertation. The case study illustrating the integration of CLV and migration probability in RFM and cluster analysis is presented in chapter 4, followed by the results of the study, discussion, and conclusions in chapter 5.

In addition, Appendix A illustrates the application of business intelligence and marketing analytics to making proper decisions in a competitor-oriented pricing environment in Complementary and Alternative Medicine (CAM) Industry utilizing the concept of RFM, cluster analysis, CLV, business intelligence, business analytics, and predictive modeling.

# CHAPTER 2

# LITERATURE REVIEW

## 2.1 Customer Lifetime Value

CLV was first introduced in the context of marketing as the present value of profit from a customer within a certain period (Berger & Nasr, 1998; Dwyer, 1997) and used to determine the revenue customers are expected to generate over their entire relationship with an enterprise (Dahana, Miwa, & Morisada, 2019; Pfeifer, Haskins, & Conroy, 2005). CLV affects the distribution of promotions, allocation of resources, and other decisions for retaining customers (Kumar et al., 2004). It is calculated differently based on assumptions which can be classified as scoring models, probability models, econometric models, and mathematic models on the basis of a financial theorem and simulation models. Scoring models employ the concepts of purchasing characteristics (Michel, Schnakenburg, & von Martens, 2017). Probability models are viewed as an expression of an underlying stochastic process and determined by individual characteristics such as the negative binomial distribution (NBD) model (Estrella-Ramon, Sanchez-Perez, Swinnen, & VanHoof, 2017; Glady, Baesens, & Croux, 2009). Mathematical models are based on a financial theorem—NPV (Gupta et al., 2006) or a Markov Chain simulation (Ferrentino, Cuomo, & Boniello, 2016).

## 2.2 Customer Lifetime Value and Customer Relationship Management

Over the past decades, relationship marketing has become one of the dominant paradigms of marketing practice and academic research (Eiriz & Wilson, 2006; Palmatier, Dant, Grewal, & Evans, 2006). Most literature has developed around the concept of customer relationship management (CRM), which changes the focus of the organization from product-centric to customer-centric (Barfar, Padmanabhan, &

Hevner, 2017; Kim, Suh, & Hwang, 2013). Customer lifetime value (CLV) is a key statistical measure in CRM used to calculate the relationship between customers and organizations with the goal of CRM maximizing the lifetime value of a customer to an organization (Farias, Torres, & Mora Cortez, 2017). Good management of customer relationships has several benefits, for example improving customer satisfaction, retention, and loyalty; higher customer profitability; value creation for the customer; customization of products and services, and lower processing costs (Fu, Chen, Shi, Bose, & Cai, 2017; Kim et al., 2013; Reinartz & Kumar, 2000, 2002). The performance of CRM activities depends on critical situational factors that influence the type of relationship. With the emphasis on CRM, it becomes vital that the companies not only understand CLV, but also rank and classify their customers based on their lifetime value, which can subsequently help the companies learn what the customers really want, provide appropriate products or services, and build trust.

Mathematically, CLV can be defined as the present value of the benefits expected from a customer, the sum of cumulated cash flows (Dwyer, 1997), or the net profit or loss to the firm from a customer over the entire life of that customer's transactions with the firm (Berger & Nasr, 1998). CLV formulas have been derived from scoring models, probability models, and mathematic models based on a financial theorem and simulation models. The scoring models such as RFM (recency, frequency, and monetary values) are based on the purchasing characteristics (Fader, Hardie, & Lee, 2005). The probability models are viewed as an expression of an underlying stochastic process determined by individual characteristics such as the negative binomial distribution model (Glady, Baesens, & Croux, 2009). The mathematic models are based on the NPV financial theorem (Gupta et al., 2006)—or on the Markov Chain simulation (Ferrentino, Cuomo, & Boniello, 2016). CLV formulas usually include a forecasted contribution margin, some form of the expected churn or retention rate, the marketing costs to acquire and support the customers, and all discounts for the time value of money over a period of time.

Personal contacts and relationships are very important, particularly in healthcare; thus, healthcare providers use CRM as a powerful tool to manage customers' or patients' interactions. Patients expect healthcare service providers to understand who they are and what they need. One of the most interesting aspects of healthcare management is the relationship management approach between a healthcare provider and patients in order to deliver the best quality of medical services, increase trust, and involve patients in decision making. In the business world, CRM is used to retain customer loyalty in order to increase revenue. This loyalty usually benefits the customers because of associated low prices and quality of customer services. Healthcare organizations have all the potential to build the same kind of relationship with patients and can offer more benefits. However, in the healthcare sector, only a few studies have looked at the calculation of customer lifetime value in a healthcare context (Zare-Hoseini, Tarokh, & Nooghabi, 2011). Most of the literature focuses on pleasing customers by constantly exceeding their expectations in terms of quality, service, value, and safety (Corbin, Kelley, & Schwartz, 2001), on health and medical tourism (Connrll, 2006; Moreira, 2014), and on marketing activities (Mirzaei, Pharm, Carter, & Schneider, 2018). However, since maintaining and creating profitability is important to healthcare organizations, they can benefit from customer lifetime value as an essential concept that encourages them to shift their focus from quarterly profits to the long-term health of their customer relationships.

## 2.3 RFM Analysis

The RFM model scales RFM attributes into 5 equal bins that are assigned the codes 0, 1, 2, 3, and 4 in ascending order; the range of each bin is equal to approximately 20% of all customers. For recency (R), the lower the R-coding, the shorter the time (in weeks, for instance) since the last purchase took place. In other words, the higher the R-Coding, the longer the time (in weeks) since the last purchase. For frequency (F), a low F-coding (count) indicates that a customer rarely places orders with the company. The higher the F-coding, the higher the number of transactions within a defined period. For the monetary (M) value, the lower the M-coding ($), the lower the amount that a customer spent within a defined period. In other words, the higher the M-coding, the higher the amount of money spent. The RFM codes are then used to calculate the RFM score. The five equal bins across these three metrics create 125 (5x5x5) different segments (Miglautsch, 2000). The advantages of the RFM model are that it is a simple and easy method that decision makers can understand and that the model can generally be applied very quickly (Marcus, 1998). Decision makers can also analyze customer value, assess customer lifetime value, and improve customer segmentation, without any assistance from computer or information systems professionals (Hu & Yeh, 2014). However, RFM analysis considers only three criteria, without considering other attributes such as the relationship between the company and its customers or churn probability. Additionally, RFM analysis cannot distinguish whether the customer's relationship with the company is long-term (a loyalty customer) or short-term. Therefore, some previous studies have attempted to develop new RFM models either by considering additional variables or excluding some of the variables according to the nature of the product or service. Many studies extended the RFM by including length (L), where *L* is defined as the number of time periods, such as days, from the first purchase to the last purchase in the database or Time (T), which is defined as time since first purchase or churn probability (C) along with the original RFM metrics (H. Chang & S. F. Tsay, 2004; Peker, Kocyigit, & Eren, 2017; Wei, Lin, Chien, & Wu, 2012).

## 2.4 Customer Migration Model

Customer migration (Berger & Nasr, 1998; Dwyer, 1997) or cohort analysis (Berger, Weinberg, & Hanna, 2003) is a concept that considers the relationship between a customer and an organization, capturing both duration dependence and purchase decision periodicity. It is used to observe the probability of customer return to the organization. Dwyer (1997) describes a customer migration model which categorizes customers into two types: "always a share" and "lost for good." For "always a share" customers, the model uses purchase recency to predict purchase behavior, assuming that a buyer can experiment with another supplier and may then return to the original supplier. Even though the buyer might enjoy different experiences with other suppliers, the probability of their returning to a longer-term relationship with the company is higher than customers with low switching costs. For the "lost for good" customers, this model assumes that a buyer is committed to a supplier permanently because of the high cost of switching to the new supplier. This group of customers is unlikely to shift to other suppliers and establishes a long-term view of the relation with the existing supplier. In a certain scenario, some groups of customers may not have repeated the order recently, meaning that they might still respond to the products or services in the future. Such movement is called customer migration, where the recency of the last purchase is used to predict the probability of repeated purchase in the future. Based on the empirical evidence of purchase recency, the purchase propensities of each recency cell are then estimated.

## 2.5 K-means Clustering

The k-means algorithm is one of the most popular and widely used clustering techniques. K-means clustering applies a standard algorithm that aims to classify objects into multiple subgroups based on the distance of the object to the cluster centroids. The k-means algorithm starts with the random generation of k central points. Then the Euclidian distance between each instance and each centroid is calculated. Each instance is then assigned to the closest centroid. In other words, each instance is assigned to the cluster whose centroid is nearest. It is an iterative approach which computes the value of centroids for each iteration of assigning the instances. The process is repeated until convergence occurs, meaning that the process is stopped when the clusters obtained are the same as those in the previous step. After the clusters are formed, the mean value of each cluster is recalculated based on the current objects in the cluster (H. Chang & S. Tsay, 2004).

## 2.6 Complementary and Alternative Medcine (CAM)

Complementary and alternative medicine (CAM) is the combination of a "Complementary" treatment used together with conventional medicine and "Alternative" is a treatment used in place of conventional medicine. CAM therapies are a group of diverse medical and health systems, practices, and products that are not currently considered to be part of conventional medicine (National Center for Complementary and Integrative Health, 2016). CAM is becoming more prevalent because it is used not only for treating illness but also for illness prevention and health promotion. CAM treatments include a variety of approaches— acupuncture, traditional Chinese, Ayurvedic, herbal, and homeopathic medicine as well as osteopathy, meditation/mindfulness, energy medicine, movement (tai chi or yoga), and massage therapy (Hung, Kang, Bollom, Wolf, & Lembo, 2015).

The data used to validate our RFM and cluster models are collected from a CAM clinic, the Panacee Medical Center, in Bangkok, Thailand. Panacee provides three main services including medical services, rehabilitation, and healthcare for the entire body at the cellular level. The focus is on the treatment of diseases such as diabetes, Alzheimer's disease, hypertension, Parkinson's, autistic disorders, and diseases caused by cell degeneration. The data for the proposed CLV and migration models come from 2,881 customers from different treatment or therapy programs and from both marketing and finance divisions. The data is explored, integrated, cleaned, and filtered for any errors, inconsistencies, extreme values, and multicollinearity

# CHAPTER 3

# METHODOLOGY

## 3.1 Data Collection

The raw data used to validate our CLV models are of 2 years of data from a CAM clinic in Bangkok, Thailand, called the Panacee Medical Center. The Center provides the holistic medical services, rehabilitation, and healthcare for the entire body at the cellular level (see Panacee Medical Center, 2014). The current business structure relies heavily on membership and non-membership relationships with its customers. The membership customers enter into a contractual relationship with the medical center depending on the treatment program. If they leave this relationship, the organization is well aware that the relationship is ended. The lifetime of each relationship is known with certainty once the buyer leaves. The duration of the relationship is closely tied to the revenue stream from the buyer; thus, the longer the lifetime of the relationship, the higher the value the organization can estimate. For the non-memberships, also called non-contractual relationships, customers receive treatment services from Panacee depending on the reputation, marketing, products and services, switching costs, promotions, and pricing policies. When customers leave, the organization may not be certain whether they have actually left the relationship. In other words, if they temporarily stop using the services at Panacee, there might be a chance for renewing their relationship in the future. Such a relationship is uncertain. However, the current marketing strategy at Panacee ignores this type of customer, prioritizes its customers based on the treatment program they purchase, and tends to use one-size-fits-all promotional tactics. With the integration of CLV models, the key findings of this dissertation can provide the decision support systems so that top management at the medical center can better understand its customers, make better decisions on resource allocation, and promote successful acquisition and retention strategies. Because of the variety of customers at the medical center, top management would like to evaluate different options and scenarios to estimate its customers' value. The data used to calculate CLV come from 2,422 customers from different treatment programs and from both marketing and finance divisions.

## 3.2 Customer Lifetime Value (CLV)

Overall, CLV models can be grouped into four classes by themes. The first two themes are based on the NPV financial theorem with contractual (finite) and non-contractual (infinite) horizons. In a contractual relationship, an organization knows when a customer leaves; thus, the lifetime of each customer is known with certainty once the customer departs. In a non-contractual relationship, an organization does not know when a customer leaves; the relationship between customer lifetime and purchase behavior is uncertain. The third theme, called the customer migration model, considers the probability that the customer will return in the following year as a part of the value estimation based on the recency of the previous-year response. The fourth theme considers the fact that none of the parameters used in the CLV calculation are deterministic; rather, they are probabilistic and are estimated from the historical data and, in a certain scenario, adjusted slightly toward either the optimistic or pessimistic values. CLV can be calculated on both an individual and or a group or segment basis. Figure 3.1 presents the overall process for how these CLV models are used in analyzing and evaluating its valuable customers once all parameters and scenarios used to calculate CLV are determined.

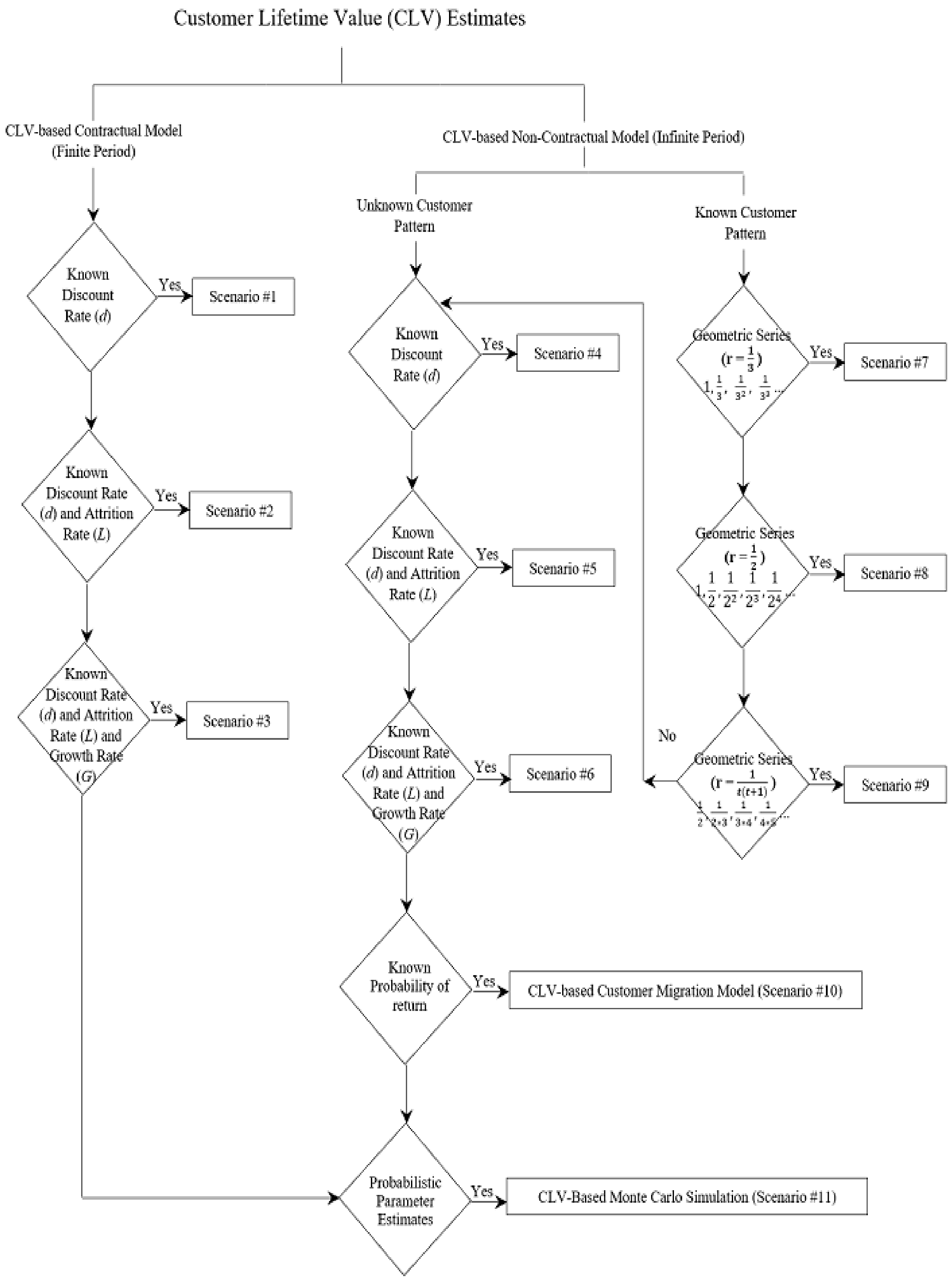



**Figure 3.1** Guidelines for CLV Estimates

## 3.3 RFM Analysis

To analyze RFM, the profile of each patient is composed of the membership number, gender, birth date, the days from the first visit date to the last visit date, the last visit date, visit frequency and monetary value of each customer including marketing campaigns as Colon Hydrotherapy and Myer's cocktail. RFM divides the customer list into five equal segments that are assigned the codes 1,2,3,4, and 5 in ascending order. The range of each segment is equal to 20% of all customers. Examples of customer clustering by classical RFM are shown in Figure 3.2.

| Transaction | Customer ID | Date to visit | Product items | Margin ($) |
|---|---|---|---|---|
| 1 | HN0001 | 2017/8/12 | Chelation, Myer cocktail, Lbaoratory | 1621.3 |
| 2 | HN0002 | 2016/4/27 | Dietary Supplement | 177 |
| 3 | HN0003 | 2017/02/26 | Myer cocktail | 916 |
| 4 | HN0001 | 2017/07/23 | Colon Hydrotherapy , B12 | 473 |
| 5 | HN0003 | 2016/05/03 | Ozone Theraphy | 2,235 |
| .... | .... | .... | .... | .... |

Calculation the RFM value of customer (Today is 2017/08/22)

R (Weeks) score: 0-1 weeks =5, 2-5 weeks = 4, 6-11 weeks = 3
12-17 weeks = 2, 18-24 weeks =1

F (Times) score: 25 times and up = 5, 14-24 times = 4, 6-13 times =3
2-5 times = 2, 1 time =1

M (Margin) score: $20,201 and up = 5, $20,200-$12,451 = 4,
$12,450 - $7,301 =3, $7,300 - $4,901 = 2, $4,900 down =1

| Customer ID. | RFM Score |
|---|---|
| HN0001 | 431 |
| HN0002 | 113 |
| HN0003 | 451 |

**Figure 3.2** Example of Customers Clustering by Classical RFM

- Recency (R) refers to the number of weeks since the last visit. The higher coding means the shorter time, in days, to the last purchase. The lower coding states the longer time to the last purchase.
- Frequency (F) refers to the number of visits in a specified time. The higher coding means more frequency (Loyalty Customer) and vice versa.
- Monetary (M) refers to amount a customer spend in a specified time. The higher coding means more spent and vice versa.

## 3.4 K-Means Clustering

K-means algorithm (MacQueen, 1967) is one of the most popular and widely used clustering techniques. It has been commonly used for clustering in various research fields (Jain, 2010). K-means algorithm starts with the random generation of k central points. Then, the distance between each instance and each centroid is calculated and each instance is assigned to the closest centroid. After the clusters are formed, the mean value of each cluster is recalculated based on the current objects in the cluster. The process is iterated until converge occurs.

# CHAPTER 4

# RESULTS AND DISCUSSION

## 4.1 Contractual (FINITE)

**Scenario #1: CLV-based NPV model with discount rate**

The simplest model is based on the concept of net present value considering the expected net cash flow from the customer over time in order to calculate the present value of that cash flow (Berger & Nasr, 1998). In Equation #1, $m$ is the margin, $d$ is the discount rate, and $n$ is the expected number of years the customer is loyal to the organization.

$$CLV_1 = \sum_{t=0}^{n} \frac{m}{(1+d)^t} \tag{1}$$

**Scenario #2: CLV-based NPV model with discount rate and attrition rate**

Considering the rate at which the company is losing customers each year (also called the churn rate or attrition rate) as a part of CLV calculation is quite common. Since the attrition rate (L), see Equation #2, is often used to determine a company's ability to retain its loyalty customers, the higher the customer attrition rate, the lower the profits the company can expect (Berger & Nasr, 1998; Dwyer,1997).

$$CLV_2 = \sum_{t=0}^{n} \frac{m*(1-L)^t}{(1+d)^t} \tag{2}$$

**Scenario #3: CLV-based NPV model with discount rate, attrition rate, and growth rate**

In addition to the discount rate and attrition rate, the growth rate is an important factor in estimating CLV. The growth rate (G) as presented in Equation #3 is usually the average percentage of margin growth based on historical records of the individual or group performance.

$$CLV_3 = \sum_{t=0}^{n} \frac{m*(1-L)^t*(1+G)^t}{(1+d)^t} \quad (3)$$

Scenarios #1 to #3, the company retains its customer group over some specified period by offering membership with an attractive volume discount for a ten-treatment program for both ozone therapy and N-acetylcysteine (Nac) therapy. The promotion is intended to appeal to female customers age 48 years and older—both Thais and medical tourists, most likely Middle Easterners—who have flu and other types of infection, cancer, hepatitis, herpes, shingles, rheumatoid arthritis, or psoriasis, and microcirculation problems or chronic ulcers. The promotion will entice customers to pay for the membership or programs over a period of approximately 5 years. On average the margin is \$200 annually. Whether or not the customers leave Panacee for other service providers depends upon the ability to retain these customers. With an estimated 8% discount rate per year (d), an average 60% attrition rate (L), and an average 80% growth rate (G) for customers who remain loyal to the company, the average CLV of this group of customers can be calculated as follows:

$$CLV_1 = \sum_{t=0}^{5} \frac{\$200}{(1+0.08)^5} = \$997$$

$$CLV_2 = \sum_{t=0}^{5} \frac{\$200*(1-0.6)^5}{(1+0.08)^5} = \$316$$

$$CLV_3 = \sum_{t=0}^{5} \frac{\$200*(1-0.6)^5*(1+0.8)^5}{(1+0.08)^5} = \$547$$

## 4.2 Non-Contractual (INFINITE)

**Scenario #4: Non-Contractual CLV-based NPV model with discount rate**

Scenario #4 is similar to the first scenario, where discount rate (d) and margin (m) are assumed to be constant throughout the customer lifetime (infinity, w). The calculation of CLV is as follows. According to the concept of geometric series (Larson & Hostetler, 2007),

$$\sum_{t=0}^{\infty} r^t = \frac{1}{1-r'} \; when\; |r| \leq 1$$

$$CLV_4 = \sum_{t=0}^{\infty} \frac{m}{(1+d)^t} \quad when\; r = \left(\frac{1}{1+d}\right), |r| < 1;$$

$$CLV_4 = m * \left(\frac{1}{1-\frac{1}{(1+d)}}\right) = m * \left(\frac{1+d}{d}\right) = m * \left(1 + \frac{1}{d}\right) \tag{4}$$

**Scenario #5: Non-Contractual CLV-based NPV model with discount rate and attrition rate**

$$CLV_5 = \sum_{t=0}^{\infty} \frac{m * (1-L)^t}{(1+d)^t} \; when\; r = \left(\frac{1-L}{1+d}\right), |r| < 1;$$

$$CLV_5 = m * \left(\frac{1}{1-\left(\frac{1-L}{1+d}\right)}\right) = m * \left(\frac{1+d}{d+L}\right) \tag{5}$$

**Scenario #6: Non-Contractual CLV-based NPV model with discount rate, attrition rate, and growth rate**

$$CLV_6 = \sum_{t=0}^{\infty} \frac{m * (1-L)^t * (1+G)^t}{(1+d)^t} \; when\; r = \left(\frac{(1-L)*(1+G)}{1+d}\right), |r| < 1;$$

$$CLV_4 = m * \left(\frac{1}{1-\left(\frac{(1-L)*(1+G)}{1+d}\right)}\right) = m * \left(\frac{1+d}{(1+d)-[(1-L)*(1+G)]}\right) \tag{6}$$

Scenarios #4 to #6 focus on a mixed selection of potential customers, those who periodically purchase a single treatment program over a long period of time and long-term customers who purchase a bundle package of several different treatment programs at a time, such as 10 chelation therapy treatments along with anti-aging or detox courses and consequently show their loyalty by extending these existing program or purchasing a new package of treatments. Both groups of customers are females 40 years old and older who have an increased risk of coronary artery disease and toxic heavy metal accumulation in the body, have undergone balloon angioplasty with a stent implant or have had bypass surgery. Even though these customers are currently very healthy, they are health-conscious, and they need chelation therapy to protect themselves from cancer or remove toxic heavy metals in the soft tissues of the body. The average margin for this group of customers is estimated at $660 annually. With an 8% discount rate, an average 50% attrition rate, and an average 80% growth rate for those who continue to have a good relationship with the medical center, CLV can be calculated as follows:

$$CLV_4 = (\$660)\left(\frac{1+0.08}{0.08}\right) = \$8{,}910$$

$$CLV_5 = (\$660) * \left(\frac{1+0.08}{0.08+0.5}\right) = \$1{,}229$$

$$CLV_6 = (\$660) * \left(\frac{1+0.08}{(1+0.08)-[(1-0.5)*(1+0.8)]}\right) = \$3{,}960$$

**Scenario #7: Non-Contractual CLV-based Geometric Series ($\boldsymbol{r = \frac{1}{3}}$)**

Scenario #7 considers a reduction in customers' margin at the rate of 1/3 annually until ∞. The term of the geometric series when the common ratio |r| is equal to 1/3 can be represented as follows:

$$CLV_7 = \sum_{t=0}^{\infty} \frac{m}{3^t} \;\; when\, r = \left(\frac{1}{3}\right), |r| < 1;$$

$$= m * \left(\frac{1}{1-\left(\frac{1}{3}\right)}\right) = m * \left(\frac{3}{2}\right) \qquad (7)$$

A majority of customers in this group are females aged 58 and over who are health consciousness and whose wellness-oriented lifestyle is driven by health-related information from reliable sources, such as healthcare professionals. These customers normally decide to purchase a high-value course such as a full medical check-up, which includes food allergy and detox courses, at once, and then continue using the services through to the end of the courses. If after-the-sale interactions and relationships are not provided, the customers might leave, switch to another medical center, or purchase fewer services. For instance, a customer joins a vascular seminar. First, she visits the company for a complete check-up course with a total margin of

$1,846. For the next visits, she purchases some therapy courses such as chelation therapy—heavy metal detox—and adds some vitamins, with margins of $615, $207, and $73, respectively. The CLV for this customer can be calculated as follows:

$$CLV_7 = \$1{,}846 + \$615 + \$207 + \$73 + \ldots + \infty$$

$$= \sum_{t=0}^{\infty} \frac{\$1{,}846}{3^t} = \frac{\$1{,}846}{(3)^0} + \frac{\$1{,}846}{(3)^1} + \frac{\$1{,}846}{(3)^2} + \frac{\$1{,}846}{(3)^3} + \ldots + \infty$$

$$= \sum_{t=0}^{\infty} \frac{\$1{,}846}{3^t} = \sum_{t=0}^{\infty} \$1{,}846 * \left(\frac{1}{1-\frac{1}{3}}\right) = \$1{,}846 * \left(\frac{3}{2}\right) = \$2{,}769$$

**Scenario #8: Non-Contractual CLV-based Geometric Series $\left(\boldsymbol{r} = \frac{\mathbf{1}}{\mathbf{2}}\right)$**

Scenario #8 considers a reduction in customers' margin at the rate of 1/2 annually until ∞. The term of the geometric series when the common ratio |r| is equal to 1/2 can be represented as follows:

$$CLV_8 = \sum_{t=0}^{\infty} \frac{m}{2^t} \;\; when\, r = \left(\frac{1}{2}\right),\; |r| < 1;$$

$$= m * \left(\frac{1}{1-\left(\frac{1}{2}\right)}\right) = 2m \qquad (8)$$

Most customers in this group are health-conscious Thai and medical tourists (mostly Chinese) ages 40 years and older. The customers in this group consider the services of the Center because of the benefits and specific privileges for short-term courses such as two-treatment courses with a basic medical check-up or a specific medical check-up. In some cases, the customers specifically request dietary supplements. For instance, a customer first visits the company for an anti-aging check-up with a total margin of $1,150. The course focuses on checking the level of hormones associated with the body's metabolic system. Later, she returns every quarter for other detox packages such as liver detox treatment, colon hydrotherapy, and ozone therapy. The estimated margin decreases by approximately one-half each time she makes a visit. The CLV for this customer can be calculated as follows:

$$
\begin{aligned}
CLV_8 &= \$1{,}150 + \$565 + \$291 + \$156 + \ldots + \propto \\
&= \sum_{t=0}^{\infty} \frac{\$1{,}150}{2^t} = \frac{\$1{,}150}{(2)^0} + \frac{\$1{,}150}{(2)^1} + \frac{\$1{,}150}{(2)^2} + \frac{\$1{,}150}{(2)^3} + \ldots + \propto \\
&= \sum_{t=0}^{\infty} \frac{\$1{,}150}{2^t} = \sum_{t=0}^{\infty} \$1{,}150 * \left(\frac{1}{1-\frac{1}{2}}\right) = \$1{,}150 * 2 = \$2{,}300
\end{aligned}
$$

**Scenario #9: Non-Contractual CLV-based Geometric Series $\left(\boldsymbol{r = \frac{1}{t(t+1)}}\right)$**

Scenario #9 considers a reduction in customers' margin at the rate of $\frac{1}{t(t+1)}$ annually until ∞. The term of the geometric series when the common ratio |r| is equal to $\frac{1}{t(t+1)}$ can be represented as follows:

$$
\begin{aligned}
CLV_9 = m + \sum_{t=1}^{\infty} \frac{m}{t(t+1)} &= m + \frac{m}{1(1+1)} + \frac{m}{2(2+1)} + \frac{m}{3(3+1)} \\
&+ \frac{m}{4(4+1)} + \cdots + \propto
\end{aligned}
$$

$$
when\ r = \frac{1}{t(t+1)'}\ |r| < 1; Let\ S = \sum_{t=1}^{n} \left(\frac{1}{t(t+1)}\right) = \sum_{t=1}^{n} \frac{1}{t} - \frac{1}{t+1}
$$

$$
S = \left(1 - \frac{1}{2}\right) + \left(\frac{1}{2} - \frac{1}{3}\right) + \left(\frac{1}{3} - \frac{1}{4}\right) + \ldots + \left(\frac{1}{n} - \frac{1}{n+1}\right) = 1 - \frac{1}{n+1}
$$

$$
when\ n = \propto, \lim_{n \to +\infty} S = \lim_{n \to +\infty} \left(1 - \frac{1}{n+1}\right) = 1
$$

$$
CLV_9 = m + \sum_{t=1}^{\infty} m \left(\frac{1}{t(t+1)}\right) = m + m * (1) = 2m
$$

This scenario is a form of cross promotion, where the customers are targeted with a co-marketing product such as a co-branded credit card. A bank may work together with the company and offer each applicant a gift voucher for a free trial course. The targeted customers are ages 28 years and older. The customers then make visits accordingly and may purchase some extra treatment packages. These customers are mostly interested in beauty or supplementary nutrition. They may decide to leave if the programs do not meet their expectations. For instance, a customer visits the company with a gift voucher and receives additional information regarding the available medical programs such as check-ups, treatments, detoxification, and vitamins and supplements. She then purchases more therapy courses with a total margin of \$328. She also purchases some other therapy courses after the first visit. The estimated margin decreases over time and the CLV of the margin can be applied as follows:

$$
\begin{aligned}
CLV_9 &= \$328 + \$176 + \$58 + \$28 + \ldots + \propto \\
&= \$328 + \frac{\$328}{1(1+1)} + \frac{\$328}{2(2+1)} + \frac{\$328}{3(3+1)} + \frac{\$328}{4(4+1)} + \ldots + \propto \\
&= \$328 + \sum_{t=1}^{\infty} \$328\left(\frac{1}{t(t+1)}\right) = \$328 + [\$328 * (1)] = \$656
\end{aligned}
$$

## 4.3 Customer Migration Model

**Scenario #10: CLV-based Customer Migration Models**

The scenarios presented in the CLV-based contractual and non-contractual models have a common assumption: that customers who leave the company are treated as new customers once they return. In other words, these models ignore the fact that customers who leave the company this year might come back the following year or the year after, although the possibility of a return might be lower across the time horizon. In this scenario, we consider the probability that customers will return in the future as a part of the CLV calculation. For instance, based on historical purchasing patterns,

- Customers who purchased any therapy program in the previous year (t-1), have a 25% probability ($P_t$) of returning in the current year, “t,” with the expected current-year purchase ($E_t$) at \$300 and the retention cost ($R_{t-1}$) of related marketing activities at \$13 per customer.

- Customers whose last purchase was in the year “t-2” have a 15% probability of returning in current year “t,” with the expected current-year purchase ($E_t$) at $240 and the retention cost ($R_{t-2}$) at $10 per customer. It is observed that when customers return after two years of absence (t-2), the average margin is lower and the money the company spends to bring them back is less than that in the first year (t-1).
- Customers whose last purchase was in the year “t-3” have a 5% probability of returning in the year “t,” with the expected current-year purchase ($E_t$) at $180 and the retention cost ($R_{t-3}$) at $5 per customer.
- Customers whose last purchase was in the year “t-4” have a 1% probability of returning in year “t,” with the expected current-year purchase (Et) at $120 and the retention cost ($R_{t-4}$) at $3 per customer.
- Customers whose last purchase was in the year “t-5” have a 0% probability of returning return in year “t”; thus, the expected current-year purchase is zero with $0 effort to bring them back.

Adapted from Berger and Nasr (1998), calculating the number of customers for each year in migration models and CLV estimations can be described as follows. The customer migration model in Figure 4.1 uses the historical data from year i = 0 to i = 4 to estimate the probability that customers will return in the future.

Customers in this scenario are driven mostly by marketing promotions and some might have high enough purchasing power to buy long-term therapy courses, such as 10 or 20 treatments per course; others might be one-time buyers when they receive good promotions such as buy-one-get-one-free or a discount of 5% to 10%. The latter tend to leave the company when other providers offer lucrative promotions or benefits. This scenario shows a customer life cycle which enables the company to refine the target customers and initiate pro-active programs that will maximize subsequent purchase opportunities. Figure 4.1 provides the probability that customers will return based on the time horizon ($P_{t-j}$), the expected purchase ($E_{t-j}$) when they come back after a certain period of time, and the retention cost of related marketing activities to bring them back ($R_{t-j}$). Figure 4.2 presents the transitions in the customer life, starting with 834 customers in 2017 (t=0). Assuming that customers who purchased any therapy program in 2017 have a 25% probability of returning in 2018, the organization can expect 209 customers will return and the other 626 customers will go to other service providers. In 2019, 52 of the 209 (25%) are still loyal and continue the services with the organization and the other 157 customers (75%) decide to leave. However, of the 626 customers who are expected to leave the organization in 2018, the probability they will return in 2019 is 15% (94 customers); the other 532 (85%) are still not promising. Table 4.2 presents an example of how to calculate the total number of customers expected to return in 2020 ($C_3$) When considering the discount rate (d) at 8% and an average 5-year lifetime span, we simply adapt the CLV estimate from Scenario #1, the CLV-based NPV model, by considering the expected number of customers retuning each year and taking into account retention costs and discount rates as presented in Figure 4.2. The total CLV of all customers is estimated at $642,558.86 or an average of approximately $770 per customer.

**Table 4.1** The Probability to Return

| **Level** | **Description** | **The Probability ($P_{tj}$) to Return in the current year "t"** | **The expected current-year purchase ($E_t$) pet- customer** | **The Retention Cost ($R_{t-j}$) in Year "t-j" per customer** |
|---|---|---|---|---|
| 1 | Customer last purchased in year "t-1" | 25% | *$300* | *$13* |
| 2 | Customer last purchased in year "t-2" | 15% | $240 | $10 |
| 3 | Customer last purchased in year "t-3" | 5% | *$180* | *$5* |
| 4 | Customer last purchased in year *"t-4"* | 1% | *$120* | *$3* |
| 5 | Customer last purchased in year "t-5" | 0% | *$0* | *$0* |

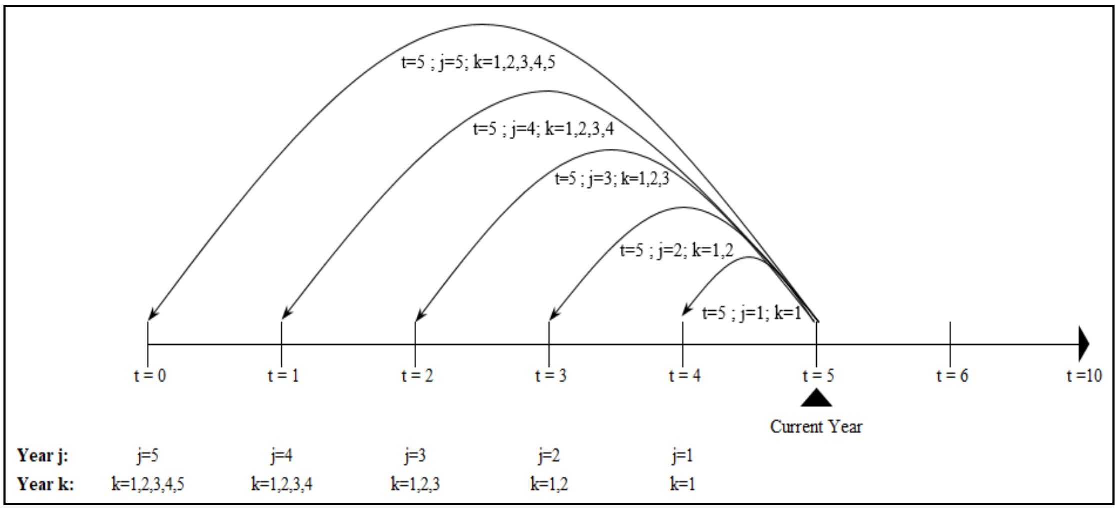



**Figure 4.1** Purchase Probabilities and Pattern and Timeline for the Customer Migration Model

$$C_i = \sum_{j=1}^{i}\left[C_{i-j} * P_{t-j} * \prod_{k=1}^{j}\left(1 - P_{t-j+k}\right)\right], with\ P_t = 0$$

Where $C_i$ is the number of customers in year *i*.

*j* is the number of previous years from year 1 to year *i* (see Figure 4.1).

*k* is the number of consecutive years in the past from 1 to year *j*.

$P_{t\text{-}j}$ is the probability that a customer will return based on the time horizon.

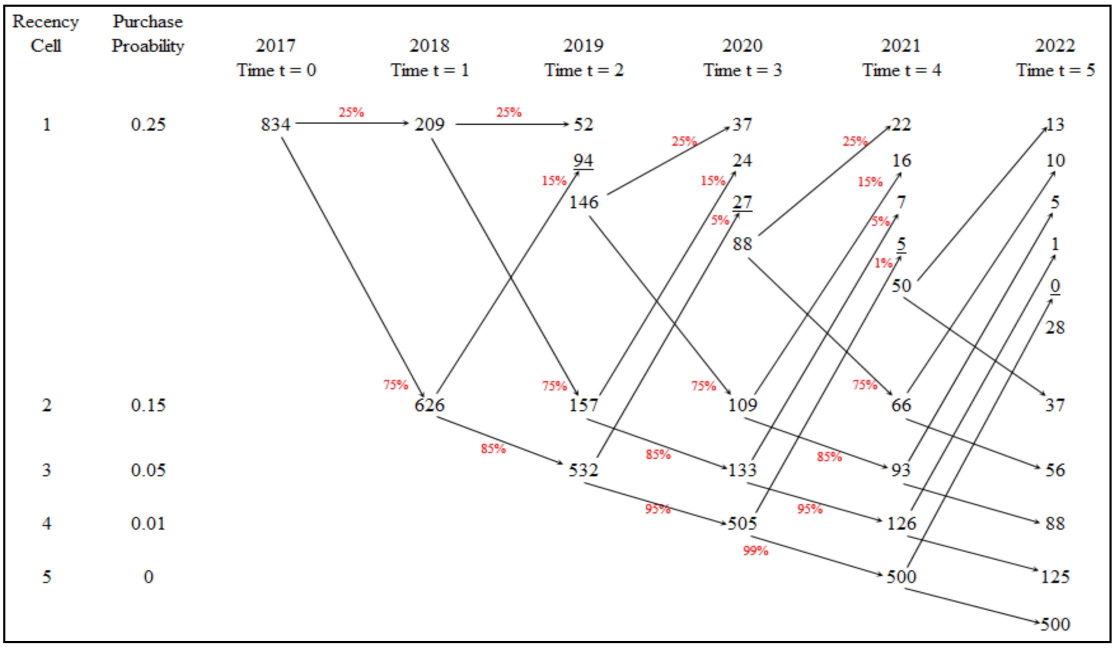



**Figure 4.2** The Transitions in Customer Life from 2017 to 2020

$$C_3 = [C_{3-1} * P_{t-1} * (1 - P_{t-1+1})] + [C_{3-2} * P_{t-2} * (1 - P_{t-2+1}) * (1 - P_{t-2+2})] + [C_{3-3} * P_{t-3} * (1 - P_{t-3+1}) * (1 - P_{t-3+2}) * (1 - P_{t-3+3})]$$

$$C_3 = [146 * 0.25 * (1 - 0)] + [209 * 0.15 * (1 - 0.25) * (1 - 0)] + [834 * 0.05 * (1 - 0.15) * (1 - 0.25) * (1 - 0)]$$

$$C_3 = 88$$

**Table 4.2** CLV Calculation with Migration Model

| **No.** | **CLV Calculation** | **Amount ($)** |
|---|---|---|
| $CLV_o$ | Total Margin in 2017 | $547,821.00 |
| $CLV_1$ | [(209*$300)-(834*$13)]/(l+0.08)$^{1}$ | $48,016.67 |
| $CLV_2$ | ([(52*$300)+(94*$240)]-[(209*$13)+(626*$10)]/(1+0.08)$^{2}$ | $25,019.72 |
| $CLV_3$ | ([(37*$300)+(24*$240)+(27*$ 180)]-[146*$13)+(157*$10)+(532*$5)])/(l+0.08)$^{3}$ | $12,377.43 |
| $CLV_4$ | ([(22*S300)+(16*S240)+(7*$180)+(5*$120)]-[(88*$13)+(109*$10)+(133*$5)+(500*$3)])/(1+0.08)$^{4}$ | $5,807.47 |
| $CLV_5$ | ([(13*300)+(10*240)+(5* 180)+(l * 120)]- [(50* 13)+(66* 10)+(93 *5)+(l 26*3)])/(1 +0.08)$^{5}$ | $3,516.57 |
| Total | | $642,558.86 |

## 4.4 Monte Carlo Simulation Model

**Scenario #11: CLV-Based Monte Carlo Simulation**

From Scenarios #1 to #10, all estimated parameters (m, d, L, and G) are deterministic and constant throughout the customer lifetime. Thus, a large portion of CLV calculation in this scenario is a simulation model run by selecting numbers randomly from a probability distribution for each parameter. In other words, in each iteration of the simulation, values are randomly generated by sampling from the probability distributions. For instance, for the period from 2014 to 2018, the company has observed that, on average, the attrition rate is estimated at 20% annually. However, the worst-case scenario was in 2016 when the attrition rate hit its highest value at 35%; since 2016, the company has improved its customer services with new staff and better after-sales service programs; thus, the attrition rates decreased significantly, from 35% to 16% and 15% in 2017 and 2018, respectively. Using the attrition rate at 20% to calculate CLV might not represent the true value of the customers. Simulation models can be useful, especially when the parameters fluctuate and are not known with certainty. In this dissertation, the Monte Carlo simulation is performed using Microsoft Excel with 1,000 simulation runs. The non-contractual

CLV- based NPV model in Scenario #6 is used to test the simulation with the probability distribution for each parameter (margin, discount rate, growth rate, and attrition rate). Computer-generated random numbers are applied along with the probability distribution for each variable. The random number generator in Microsoft Excel is expressed as “=RAND()” and uniformly returns a random number between 0 and 1 (Anderson, Sweeney, Williams, Camm, & Cochran, 2018). Thus, in each simulation run, the returned value of the random number generator results in obtaining the value of each parameter randomly depending on the probability distribution. A histogram of the CLV along with the descriptive statistics (minimum, maximum, average, and standard deviation) are presented to provide an overview of the CLV estimation.

| Cumulative Probability | | |
|---|---|---|
| Lower Random No. | Upper Random No. | Attrition Rate |
| 0 | 0.1 | 30% |
| 0.1 | 0.3 | 40% |
| 0.3 | 0.7 | 50% |
| 0.7 | 0.9 | 60% |
| 0.9 | 1 | 70% |

| Cumulative Probability | | |
|---|---|---|
| Lower Random No. | Upper Random No. | Growth Rate |
| 0 | 0.05 | 15% |
| 0.05 | 0.1 | 20% |
| 0.1 | 0.2 | 25% |
| 0.2 | 0.3 | 30% |
| 0.3 | 0.4 | 35% |
| 0.4 | 0.8 | 40% |
| 0.9 | 0.95 | 45% |
| 0.95 | 1 | 50% |

| Margin (m) | Value |
|---|---|
| Min | $1,504 |
| Most Likely | $5,500 |
| Max | $14,453 |

| Discount Rate | |
|---|---|
| Smallest Value | 8% |
| Largetst Value | 9% |

Margin (*m*) is in the form of a triangular distribution with the minimum, most likely, and maximum values of $1,504, $5,500, and $14,453.

Margin = IF(RAND()<=(Most likely – Min) / (Max – Min), [Min + (SQRT(RAND())*(Max – Min)*(Most likely – Min))], [Max – (SQRT ((1-RAND()*(Max – Min)*(Max - Most likely))]

= IF(RAND()<=($5,500 – $1,504) / (Max – $1,504), [$1,504 + (SQRT(RAND())*($14,453 – $1,504)*( $5,500 – $1,504))], [$14,453 – (SQRT ((1-RAND()*($14,453 – $1,504)*( $14,453 - $5,500))]

Discount Rate (*d*) is in a uniform distribution between 8% and 9%.

Discount Rate = Min + [(Max – Min)*RAND()] = 0.08 + [((0.09 – 0.08)*RAND())]

Attrition rate (*L*) ranges from 30% to 70% and growth rate(G) ranges from 15% to 50%

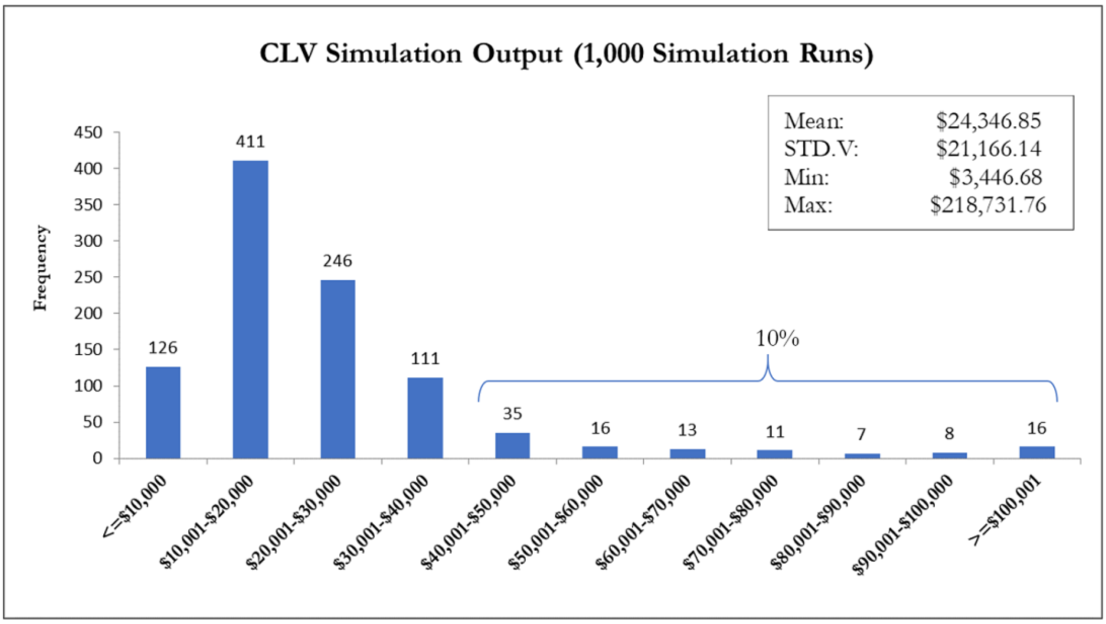



**Figure 4.3** CLV-based Monte Carlo Simulation

This Monte Carlo Simulation scenario lets top management see all possible outcomes of CLV and assess the impact of risks for every parameter estimate, which allows for better decision-making under uncertainty. Each parameter has a different probability distribution. For example, below are some of the more realistic values describing uncertainty in each parameter for the loyalty-premium customers, those who have participated in the treatment programs such as chelation and Myers' Cocktail and have been with Panacee Medical Center for over three years.

A histogram of simulated CLV (1,000 runs or trials) is shown in Figure 4.3. Each simulation run involves randomly generating values for the margin, discount rate, attrition rate, and growth rate and computing CLV. The distribution of CLV has quite a long right tail, with a large number of values in the range of $3,446.68 to $218,731.76 and an average value of $24,346.85.

## 4.5 RFM Analysis

**Scenario #12: RFM Analysis**

***Customer Lifetime Value (CLV)***

CLV is used to evaluate a customer's worth by demonstrating the present value of the future profit stream that an enterprise can expect to receive from the customer over a given time horizon (Kumar, 2010). This dissertation uses the basic model, which calculates customer lifetime value using the customer's historical data and taking into account their future account. Equation #9 presents the CLV model, where *m* is the margin ($), *d* is the discount rate, and *n* is the number of years the customer is expected to be loyal to the organization. The assumption is that both the margin and discount rate are, on average, constant throughout the customer's lifetime.

$$CLV\ (\$) = \sum_{t=0}^{n} \frac{m}{(1+d)^t} \tag{9}$$

The average length of time a customer spends with a healthcare-related business is estimated at 10 to 15 year period (Heper, 2013). Thus, in this dissertation, *n* is estimated at 15 years. With an estimated 8% discount rate per year, the CLV estimation for a customer (ID HN 00071) with an average margin of $200 annually over a period of approximately 5 years and the growth rate at 1.5% can be calculated as follows:

$$CLV\ (\$) = \sum_{t=0}^{15} \frac{\$200 * 1.015^{15}}{(1 + 0.08)^{15}} \approx \$2{,}092$$

***RF(M=CLV) Model***

The original RFM model scales each attribute into 5 equal bins that are assigned the codes 0 to 4 in ascending order. The RFM codes for each observation are then used to calculate the RFM score as presented in Equation #10

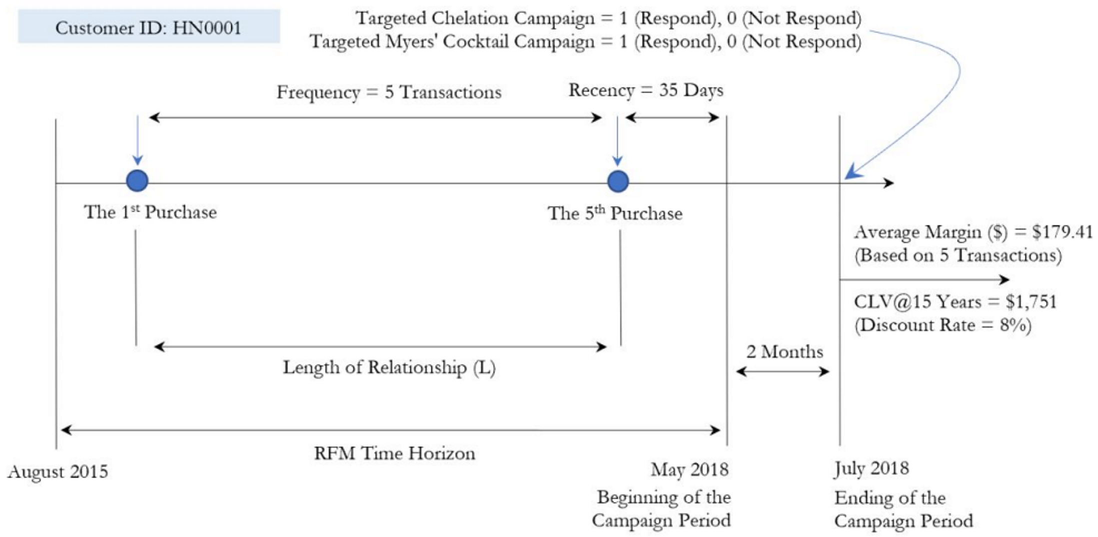
RFM Score = 100*(5-Recency) + 10*(Frequency+1) + (CLV+1) --- (10)

The twelve scenario integrates CLV into the original RFM model by substituting CLV for the original monetary value (M) to for the future value of the customers. Figure 4.4 presents an example of the RFM Coding, where the “R = 0” range is from 1 to 313 days and “R = 4” ranges from 869 to 1,083 days; the “F = 0” range is from 1 to 2 transactions within 3 years and “F = 4” refers to the number of transactions greater than 12 and up to 46 times; the “CLV = 0” range is below $564 and “CLV = 4” refers to lifetime values between $12,105 and $49,481 over 15 years.

- The last time Customer ID “HN0001” visited Panacee Medical Center for a treatment was 35 days ago. In the past three years, he/she purchased a total of 5 treatment programs with an estimated CLV of $1,751. According to the RFM Coding in Figure 4.4, “R” is coded as “0.” “F” is coded as “2,” and “M” is coded as “1.” More importantly, this customer did actually participate in both promotional Chelation and Myers’ Cocktail campaigns. The RFM Score for Customer ID “HN0001” (R = *0*, F = *2*, and M = *1*) is equal to 532, which is derived from 100*(5-*0*) + 10*(*2*+1) + (*1*+1).
- Customer ID “HN0002” has an RFM Score of 311 (R = *2*, F = *0*, and M = *0*). He/she responded only to the Myers’ Cocktail campaign. However, Customer ID “HN0003,” who has an RFM Score of 444 (R = *1*, F = *3*, and M = *3*), did not responded to any of the proposed campaigns.

| R | R-Range (Days) | R (% Observations) | F | F-Range (Count) | F (% Observations) | M | CLV-Range ($) | M (% Observations) |
|---|---|---|---|---|---|---|---|---|
| 0 | 1 - 313 | 0 - 20 | 0 | 1 - 2 | 0 - 20 | 0 | ≤ $564 | 0 - 20 |
| 1 | 314 - 483 | 20 - 40 | 1 | 3 | 20 - 40 | 1 | $564 - $1,854 | 20 - 40 |
| 2 | 484 - 687 | 40 - 60 | 2 | 4 - 5 | 40 - 60 | 2 | $1,855 - $4,570 | 40 - 60 |
| 3 | 688 - 868 | 60 - 80 | 3 | 6 - 11 | 60 - 80 | 3 | $4,571 - $12,104 | 60 - 80 |
| 4 | 869 - 1,083 | 80 - 100 | 4 | 12 - 46 | 80 - 100 | 4 | $12,105 - $49,481 | 80 - 100 |

| Customer ID | Recency (Days) | Frequency (Counts) | CLV ($) | RFM Coding | | | | Targeted Campaigns | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | R | F | M | RFM | Chelation | Myers' Cocktail |
| HN0001 | 35 | 5 | $1,751 | 0 | 2 | 1 | 532 | 1 | 1 |
| HN0002 | 621 | 2 | $519 | 2 | 0 | 0 | 311 | 0 | 1 |
| HN0003 | 322 | 6 | $5,432 | 1 | 3 | 3 | 444 | 0 | 0 |




| RFM | No. of Customers | % Customers | Gender | Average Age | Nationality | Average CLV ($) | No. of Customers Purchasing "Chelation" | % Response | No. of Customers Purchasing "Myers' Cocktail" | % Response |
|---|---|---|---|---|---|---|---|---|---|---|
| 111 | 101 | 5% | F (61%) M (39%) | 48 | Thai (63%) Chinese (37%) | $266 | 11 | 11% | 11 | 11% |
| 113 | 54 | 3% | F (78%) M (22%) | 50 | Chinese (76%) Thai (15%) | $3,163 | 1 | 2% | 30 | 56% |
| 134 | 17 | 1% | F (53%) M (47%) | 57 | Thai (29%) Qatari (29%) Chinese (18%) | $9,467 | 0 | 0% | 9 | 53% |
| … | … | … | … | … | … | … | … | … | … | … |
| 232 | 17 | 1% | F (76%) M (24%) | 49 | Thai (41%) Chinese (35%) | $1,379 | 3 | 18% | 6 | 35% |
| 253 | 9 | 1% | F (44%) M (56%) | 52 | Thai (78%) American (22%) | $3,851 | 5 | 56% | 3 | 33% |
| … | … | … | … | … | … | … | … | … | … | … |
| 333 | 26 | 1% | F (81%) M (19%) | 44 | Chinese (38%) Thai (15%) | $3,511 | 2 | 8% | 6 | 23% |
| … | … | … | … | … | … | … | … | … | … | … |
| 435 | 12 | 1% | F (50%) M (50%) | 49 | Thai (33%) Other (77%) | $24,772 | 0 | 0% | 10 | 83% |
| … | … | … | … | … | … | … | … | … | … | … |
| 554 | 32 | 2% | F (47%) M (28%) | 47 | Thai (72%) Chinese (9%) | $11,218 | 16 | 50% | 19 | 59% |
| 555 | 99 | 5% | F (57%) M (43%) | 52 | Thai (58%) Bangladeshi (14%) | $61,084 | 48 | 48% | 66 | 67% |

**Figure 4.4** RFM Coding with Targeted Campaigns

Based on the RFM score, there is no guarantee that the customers in a certain RFM group are likely to respond to the proposed campaigns. Thus, the next step is to group all customers based on the RFM scores, calculate the summary statistics on the number of customers in each group and, subsequently, calculate the % rate of response to the Chelation and Myers' Cocktail campaigns of the customers for each RFM group separately. As presented in Figure 4.4, RFM Group #111 has a total of 101 customers (approximately 5%), with an average age of 48 years. Most of them are Thai (63%). About 11 % respond equally to both Chelation and Myers' Cocktail campaigns. Of the 54 customers in RFM Group #113, only 1 (2%) and 30 (56%) customers respond to the Chelation and Myers' Cocktail campaigns, respectively. Customers in RFM Group #435 are likely to respond to the Myers' Cocktail campaign, with a response rate of 83%.

Theoretically, customers in RFM Groups #111 to #113 (R=4 F=0, and M=0 to 2) are considered inactive; they spend little and are infrequent buyers in the eyes of top management. If top management evaluates its customers based only on the RFM score, these customers will be ignored and get less priority as opposed to the loyalty and high value customers in RFM Group #555 (active, high spending, and frequent buyers). Considering the following example, the expected margin for a Myers' Cocktail treatment program is estimated at $130. The medical center expects a total of 200 customers to be classified into RFM Group #113. By assuming the same response rate, at 56% (as presented in Figure 4.5), the opportunity loss if top management ignores customers in this group for the targeted Myers' Cocktail treatment program can be calculated as follows:

The Opportunity Loss = Expected Margin * Response Rate * Expected No. of Customers

= $130 * 56% * 200

= $14,560

The underlying assumption is that the future purchasing behavior of customers resembles the past and current purchasing behavior. Thus, if the goal is to identify target market groups of customers who are likely to purchase the Chelation treatment program, with the cut-off point of greater than 50%, customers in RFM groups #253 and #554 will be good candidates, as the response rates are higher than 50%. When the cut-off point is set higher, at 80% for instance, for the Myers' Cocktail program, the customers in RFM Group #435 are the only option. However, there are several concerns regarding the deployment of the RFM model to justify the right target groups to optimize marketing strategies. Not only are customers not equally classified in each RFM group, the RFM model ignores the fact that customer behavior is changing all the time. The assumption that the best buyers in the RFM groups will remain the best responders or continue the same engagement level in the future may hold in general, but marketing analysts cannot rely only on the RFM model as a best practice to develop marketing strategies. Scenario #13 addresses these issues by utilizing k-mean clustering techniques integrating the RFM attributes, length of the relationship, and migration probability into the model.

## 4.6 Cluster Analysis with CLV and Customer Migration

**Scenario #13: Cluster Analysis with CLV and Customer Migration**

***Customer Migration Model***

One of the key assumptions in market segmentation is that it is possible that customers who temporarily switch to other competitors this year might return to the company the following year or the year after. In other word, customers who purchased the treatment program in 2014 might not repeat the same program or pay for any other programs in the second year (2015) or the third year (2016) but decide to come back in the fourth year (2017) or the fifth year (2018). The probability of return decreases across the time horizon. In other words, the probability that customers will return next year will be higher than that for the following year.

Based on historical purchasing patterns from 2014 to 2019 (see Figure 4.5), of 550 customers who purchased the Chelation and Myers' Cocktail treatment programs in 2014 ($T_{i=0}$), 138 continued their relationship with Panacee in 2015 ($T_{i=1}$). That means that customers who were active in the previous year, ($T_{i-1}$), have approximately a 25% probability ($P_{i-1}$) of returning in the current year, "i." Of 138 customers in 2015, 35 customers (approximately 25%, $P_{i-1}$) returned in 2016 ($T_{i=2}$) but 103 customers (approximately 75%) did not. The medical center still spent quite a lot to retain the

412 customers who left completely or temporarily stopped using the services in 2015. It was observed that of these 412 customers, 62 customers returned to the business in 2016 ($T_{i-2}$). That means that customers whose the last purchase was in the year "$T_{i-2}$" have approximately a 15% probability ($P_{i-2}$) of returning in the current year, "i."

Similarly, of 97 customers in 2016, 24 customers were still active in 2017 ($T_{i-3}$); meanwhile, 15 of 103 customers who left in 2016 ($T_{i-1}$), and 18 of 350 customers who had been inactive for two consecutive years, since 2015 ($T_{i-2}$), returned to the business in 2017. This pattern implies that customers who were loyal to the company in the previous year ($T_{i-1}$), still have an approximately 25% probability ($P_{i-1}$) of returning in current year "i." Those customers whose last purchase was in the year "$T_{i-2}$" have a lower chance of returning, at 15% ($P_{i-2}$), and even lower, at 5% ($P_{i-3}$), if their last purchase was in the year "$T_{i-3}$." Following a similar pattern, we can surmise that customers whose last purchase was in years "$T_{i-4}$" and "$T_{i-5}$" have 1% ($P_{i-4}$) and 0% ($P_{i-5}$) probabilities of returning in year "i," respectively.

Equation 11 depicts the customer migration model, which uses the historical data from year i = 0 to i = 4 to estimate the number of customers that will return in 2019.

$$C_i = \sum_{j=1}^{i} \left[ C_{i-j} * P_{t-j} * \prod_{k=1}^{j} \left(1 - P_{t-j+k}\right) \right], with\ P_t = 0 \tag{11}$$

Where $C_i$ is the number of customers in year $i$.
$j$ is the number of previous years from year 1 to year $i$.
$k$ is the number of consecutive years in the past from year 1 to year $j$.

$P_{t-j}$ is the probability that a customer will return based on the time horizon. Below is an example of how to calculate the total number of customers expected to return in 2019, which is then used to evaluate whether the probability that customers are returning in 2019 is consistent at 25%, 15%, 5%, and 1% respectively throughout the time horizon.

$$C_i = \sum_{j=1}^{i}\left[C_{i-j} * P_{t-j} * \prod_{k=1}^{j}\left(1 - P_{t-j+k}\right)\right], with\ P_t = 0$$

$$\begin{aligned}
C_5 = {} & [C_{5-1} * P_{t-1} * (1 - P_{t-1+1})] \\
& + [C_{5-2} * P_{t-2} * (1 - P_{t-2+1}) * (1 - P_{t-2+2})] \\
& + [C_{5-3} * P_{t-3} * (1 - P_{t-3+1}) * (1 - P_{t-3+2}) * (1 - P_{t-3+3})] \\
& + [C_{5-4} * P_{t-4} * (1 - P_{t-4+1}) * (1 - P_{t-4+2}) * (1 - P_{t-4+3}) \\
& * (1 - P_{t-4+4})] \\
& + [C_{5-5} * P_{t-5} * (1 - P_{t-5+1}) * (1 - P_{t-5+2}) * (1 - P_{t-5+3}) \\
& * (1 - P_{t-5+4}) * (1 - P_{t-5+5})]
\end{aligned}$$

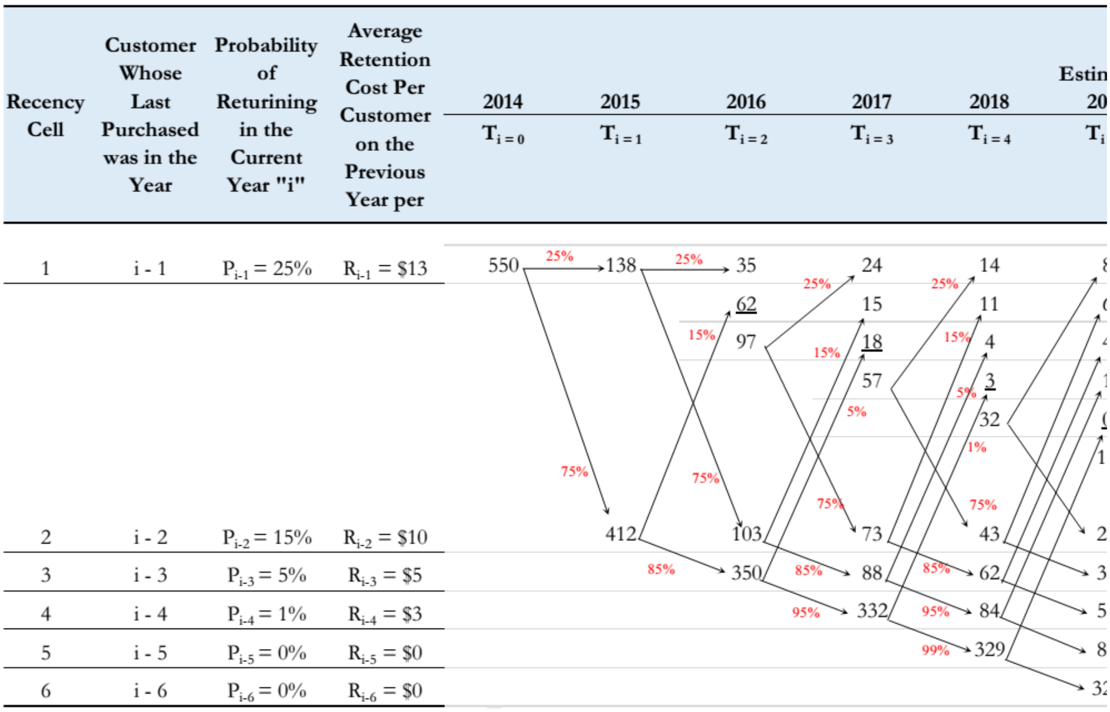
$$\begin{aligned}
C_5 = {} & [32 * 0.25 * (1 - 0)] + [57 * 0.15 * (1 - 0.25) * (1 - 0)] \\
& + [138 * 0.05 * (1 - 0.15) * (1 - 0.25) * (1 - 0)] \\
& + [550 * 0.01 * (1 - 0.05) * (1 - 0.15) * (1 - 0.25) \\
& * (1 - 0)]
\end{aligned}$$

$$C_5 = 19$$

The company spent approximately $13 on average per person to retain its customers who participated in the treatment program in the previous year ($T_{i-1}$). The amount of spending allocated for those whose last purchase was in the year “$T_{i-2}$” was lower, at $10 per customer; in the year “$T_{i-3}$” it was $5 per customer; in “$T_{i-4}$” $3 per customer; and in “$T_{i-5}$” $0.

## 4.7 K-Means Clustering

The thirteen scenario extends the proposed RF(M=CLV) model in Scenario #1 by considering the length of the relationship (L), which refers to the number of days from the first to the last visit, and the migration probability. The description of attributes used in the k-mean clustering model is presented in Figure 4.5. Additionally, to make the interpretation simpler, in Figure 4.6 the arrows **“j”** and **“t”** are used when the attributes (L, R, F, and M) for any clusters are below and above the average values.




| Attributes | Minimum | Maximum | Mean |
|---|---|---|---|
| L (Length) (Days) | 1 | 1,135 | 200 |
| R (Recency) (Days) | 1 | 1,073 | 424 |
| F (Frequency) (Times) | 1 | 48 | 7 |
| M (Customer Value) ($) | $16 | $55,618 | $8,605 |

| Recency Cell | Description | Migration Probability |
|---|---|---|
| 1 | Customers whose last purchased were in year "$T_{i-1}$" | $P_{i-1}$ = 25% |
| 2 | Customers whose last purchased were in year "$T_{i-2}$" | $P_{i-2}$ = 15% |
| 3 | Customers whose last purchased were in year "$T_{i-3}$" | $P_{i-3}$ = 5% |
| 4 | Customers whose last purchased were in year "$T_{i-4}$" | $P_{i-4}$ = 1% |
| 5 | Customers whose last purchased were in year "$T_{i-5}$" | $P_{i-5}$ = 0% |
| 6 | Customers whose last purchased were in year "$T_{i-6}$" | $P_{i-6}$ = 0% |

**Figure 4.5** Customer Migration Model from 2014 to 2019

Figure 4.6 presents the profiles of each cluster for the targeted Chelation and Myers' Cocktail campaigns.

- Customers in Cluster #1 are mostly Thai females, 45 years old with a moderate relationship length. They are considered "Lapsing Customers," responding to campaigns occasionally with lower-than-average transaction counts and relatively low customer lifetime values. Most of them are in the first tier of migration probability to return next year. The probability that they will respond to the Chelation and Myer's Cocktail campaigns is 14.96% and 32.30%, respectively.

- Customers in Cluster #2 are considered "Loyalty Customers" and have an average age of 53 years. They are long-time customers with the highest average length of relationship, the highest transaction counts, and relatively high customer lifetime values. Approximately 3/4 of customers in this group are in the first tier of migration probability, and the probability that they will respond to the Chelation and Myer's Cocktail campaigns is 34.67% and 36.67%, respectively.

- Customers in Cluster #3 are considered "Potential Customers," since they are relatively new to the company (lower-than-average length of relationship) compared to customers in the Clusters #1 and #2. The average recency for customers in this group is also lower than the overall average. Although they have not purchased a lot of treatment programs, they are among the highest value customers. Three-fourths of the customers in this group are also in the first tier of migration probability. The probabilities they will respond to both the Chelation and Myer's Cocktail campaigns are slightly higher than those of the customers in the first group.

- Customers in Cluster #4 are a lower priority to the company; they have the lowest customer lifetime values, the shortest length of relationship, the lowest transaction counts, and the longest period since their last purchase. These customers can be called frugal customers, and most of them are in the second and third tiers of migration probability. The probability these customers will respond to both Chelation and Myer's Cocktail campaigns is among the lowest compared to the other clusters.

For all four clusters, most customers are female; however, it is possible for male customers to be in the Loyalty and Potential cluster groups (Clusters#2 and #3) for the targeted treatment campaigns. More focus can be on the Bangladeshi, followed by the Qatari and Chinese, customers. The customers in Cluster #4 usually are either one-time purchasers or tourists from exhibitions or booths at major events in which the enterprise has participated.

**Table 4.3** Clustering Results and Customer Profile

| Customer Characteristic | Cluster 1 | Cluster 2 | Cluster 3 | Cluster 4 |
|---|---|---|---|---|
| Cluster Name | Lapsing Customers | Loyalty Customers | Potential Customers | Economical Customers |
| No. of Customers | 548 (34%) | 150 (9%) | 196 (12%) | 698 (44%) |
| LFRM Pattern | L↑R↓F↓M↓. | L↑ R↓F↑M↑ | L↓R↓F↓M↓ | L↓R↑F↓M↓ |
| Gender (M/F) | F 354 (65%)<br>M 194 (35%) | F 88 (59%)<br>M 62 (41%) | F 98 (50%)<br>M 98 (50%) | F 455 (65%)<br>M 243 (35%) |
| Avg. Age (Years) | 45 | 53 | 52 | 49 |
| Avg. Length (Days) | 253 | 708 | 121 | 72 |
| Avg. Recency (Days) | 173 | 230 | 235 | 716 |
| Avg. Transaction Counts | 6 | 26 | 7 | 4 |
| Average CLV ($) | $4,469 | $21,949 | $25,917 | $4,123 |
| Migration Probability (%) | No. of Customers | No. of Customers | No. of Customers | No, of Customers |
| $P_{i-1}$ = 25% | 512 (93%) | 114(76%) | 147 (75%) | 49 (7%) |
| $P_{i-2}$ = 15% | 36 (7%) | 34 (23%) | 41 (21%) | 287 (41%) |
| $P_{i-3}$ = 5% | | 2 (1%) | 8 (4%) | 362 (52%) |
| Nationality | Thai (52%)<br>Chinese (8%)<br>Qatari (3%) | Thai (75%)<br>Bangladeshi (8%)<br>Qatari (6%) | Thai (35%)<br>Bangladeshi (10%)<br>Qatari (9%) | Diai (50%)<br>Chinese (20%)<br>Qatari (6%) |
| Treatment Programs | Chelation (14.96%)<br>Myer's Cocktail (32.30%) | Chelation (34.67%)<br>Myer's Cocktail (36.67%) | Chelation (19.90%)<br>Myer's Cocktail (37.24%) | Chelation (10.74%)<br>Myer's Cocktail (31.09%) |

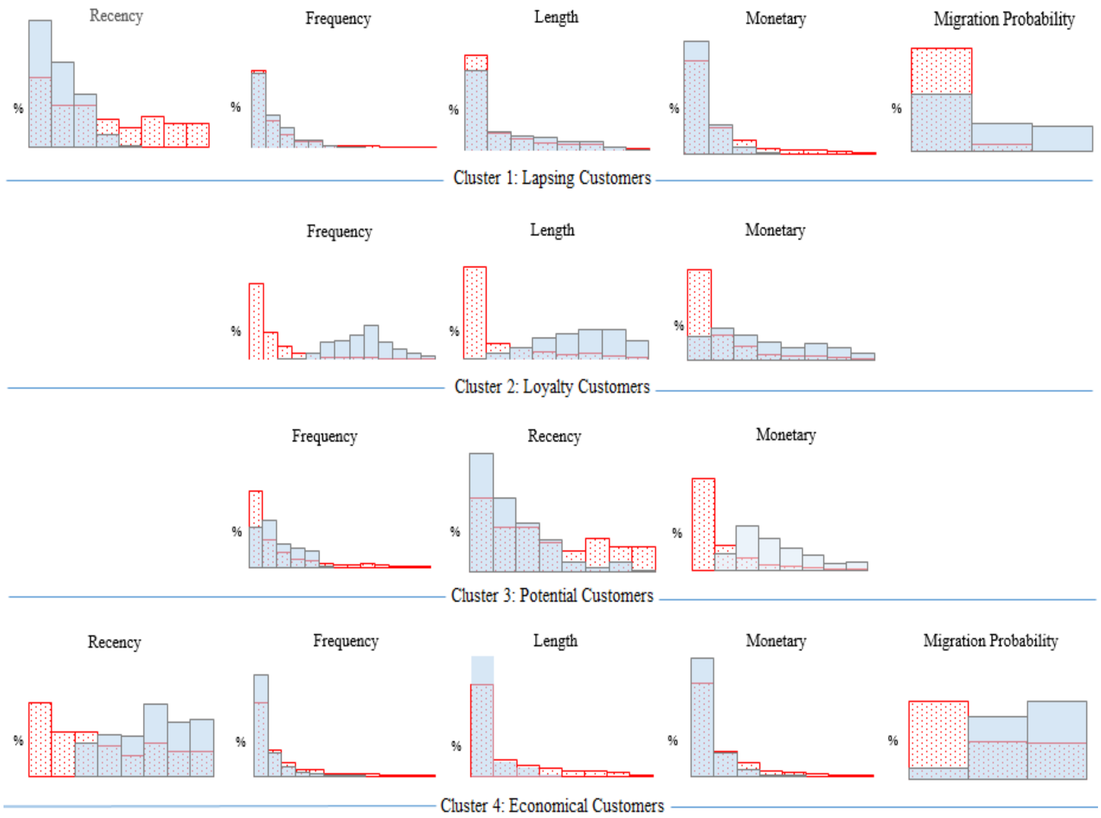



**Figure 4.6** Cluster Profiles for the Targeted Chelation and Myers' Cocktail Campaigns

# CHAPTER 5

# CONCLUSION

## 5.1 Conclusion

Because of extensive competition from other providers, many organizations strive very hard to retain their loyalty customers, allocate and utilize their limited resources to a target group of customers, and promote the right campaigns and promotions to the right groups of customers. Thus, it is important to recognize and prioritize both important and less-important potential customers so that proper strategies can be initiated. Customer lifetime value (CLV) is a key measurement of how valuable a customer is to the company over the customer's entire relationship with the company. Understanding CLV can help any organization develop strategies not only to attract new potential customers but to retain the existing ones as well, while maintaining profit margins.

The first part of this dissertation, we divide the CLV models into 4 groups by themes and consider the discount rate, attrition rate, growth rate, probability that customers will return in the future, and probabilistic rather than deterministic parameter estimates. The four themes are the CLV-based contractual model with a finite period, the CLV-based non-contractual model with an infinite period, the CLV-based customer migration model, and the CLV-based Monte Carlo Simulation. A case study implementing CLV to support marketing decisions in the complementary and alternative medicine (CAM) industry is conducted to validate our models. The results show that understanding CLV and keeping track of this metric along with other business performance indicators as shown in the executive dashboard is an effective way to get a sense of what is driving customer spending, and how loyal each group of customers is to the company.

For contractual customers who are part of the long-term treatment programs, the push strategy can be employed. Basically, the medical center focuses on sales promotions by means of personal selling or individualized campaigns through product differentiation to ensure that the recommended treatment programs reach the targeted customers. Service differentiation through physicians and well-trained staff must be emphasized to enhance customer experience and improve the quality of service. In the case of medical tourism, where the services are often distributed through an agency, promotional efforts aimed at convincing these agencies to recommend or reserve a service should be part of the strategic planning.

For a group of new customers with a relatively high CLV potential, greater than $1,000, the pull strategy, which aims to induce customers to participate in treatment programs and request more services by means of direct advertising in the mass media, direct mail, sale promotions, and publicity, is needed. The pull strategy is intended to educate and promote products and services, to create awareness, to stimulate self-referrals, and consequently, to pull products towards these customers. Social media such as Line, Facebook, and YouTube, along with health magazines and TV sponsorships are alternatives to attract customers, help them understand existing and upcoming products and services, and increase their lifetime value. For non-contractual customers who continue to have a good relationship with the company, a loyalty program should be in place in an effort to retain the high value customers, track individuals' progress, and reduce the cost of marketing practices to bring them back.

When assessing the strategies to acquire new customers or retain existing customers, if a strategy costs more than the CLV estimates, the company is potentially losing money and such strategies might not be worthwhile. In other words, when retention or acquisition costs become too high, the company risks losing regardless of how high the CLV is. In fact, top management can even spot the early signs of customers' churn when the current CLV estimate for a group of customers is decreasing compared to that from the previous estimate, which may be the result of a drop-off in the average margin of that group.

Moreover, the second part of this dissertation demonstrates how to integrate both customer lifetime value and customer migration to improve RFM and clustering models. Traditionally, some customers are theoretically considered to have less priority or are ignored when they rarely respond to campaigns, when they spend less, or when they have been inactive for a certain period. By considering both the future value of customers and the probability that a customer will return in the following year, some groups of customers signal to top management that they have potential value or are likely to return to the business sooner rather than later. In other words, the predetermined group of high-profile customers based on RFM score and cluster analysis might not always have a higher response to a specific campaign than low-profile customers because of behavioral segmentation patterns related to differences in the campaigns, promotions, services, and products the enterprise has initiated.

The first RF(M=CLV) Model provides an idea as to which customers can be classified as loyalty customers, big spenders, and low-spending customers and helps enterprises detect whether they are about to lose their loyalty customers. The second clustering model, which includes recency, frequency, length of relationship, CLV, and migration probability, helps strengthen the decision to prioritize and categorize customers as lapsing, loyalty, potential, and frugal. In either scenario, the marketing strategies are analyzed based on different targeted campaigns such as the Chelation and Myer’s Cocktail treatment programs in this dissertation.

Some might argue that using only transaction-based data to perform cluster analysis cannot effectively segment customers that share similar characteristics, as opposed to clustering models with more factors such as demographic information, perception-based data, product characteristics, and sales and marketing related data. First, this dissertation focuses on utilizing data that is available on hand without requiring further data collection. Second, the scenarios presented depict the calculation of CLV and migration probability and their implications for RFM and cluster analysis. The more complex CLV estimation considering growth and attrition rates, for instance, is recommended if the objective is to differentiate customers deeply based on their values. Additionally, both CLV and migration probability can always be considered as significant dimensions or factors in any more complex segmentation models. Third, the CAM-related healthcare industry is unique and customers reacting to the treatment programs may be different from those responding to retail campaigns. The outcomes of RFM and cluster analysis may result in extreme cases, even when a small finding on customers' characteristics helps shape the direction of the enterprise. Last, the results of this dissertation show that keeping track of these metrics with the proposed executive dashboard is an effective way to get a sense of the behavioral purchasing patterns of customers at a glance and to determine which factors are driving customers' spending and loyalty

## 5.2 Managerial Implication

Several implications are found in this dissertation. According to figures 5.1 and 5.2 present the first design-stage of executive dashboards to aid in decision making. Top management can utilize the CLV models to justify the decision choices; for instance, what marketing approaches can be used for a customer purchasing a Myer's Cocktail treatment program? Or based on the customer satisfaction score and a lifetime values in the range between $1,000 and $8,000, should Panacee offer this customer the bundled packages of liver detox and colon hydrotherapy treatment? Or what exclusive treatment packages are designed specifically for a group of customers who have CLV estimates over $10,000? Below is an example of feedback from the CEO of the medical center when he evaluated the executive dashboard and the CLV models:

> As an executive, I strongly agree that customer lifetime value is important, especially for organizations like us that focus on building good relationships with customers. I believe that customer value can help us and allow us to plan in the future to support our business growth
>
> Yuranunt Pamornmontri, The chairman and CEO of Panacee Medical Center

Figure 5.3 present the proposed executive dashboards developed and customized to aid top management in decision making. This dashboard is intended to serve as a patient-centric display for Panacee, consolidating all relevant data into a single frame. The metrics included in the dashboard can be categorized into 5 sections: RFM analysis, cluster analysis, patients' information, details on the products by each segment, and proposed marketing strategies. Below is an example of feedback from the CEO of the medical center when he evaluated the executive dashboard and the segmentation models:

> In terms of segmentation, I think it is a good thing. It is like a guideline to make us know and understand more about our customers. As an executive, I am able to get my staff to take care of our clients and to be closer to them.
>
> Yuranunt Pamornmontri, The chairman and CEO of Panacee Medical Center

A marketing analyst can start by interpreting the RFM results to understand the medical center's customers. For instance, customers in RFM group "555" (R=0, F=4, and M=4) seem to be the best customers as they have bought most recently and most often and have spent the most. Customers in any RFM groups "X5X" (R=X, F=4, and M=X) are considered "Loyalty Customers" since they buy the most frequently. Customers in any RFM groups "XX5" (R=X, F=X, and M=4) are considered "Big Spenders" since they spend the most compared to the other groups. Interestingly, the signals in RFM groups "155" (R=4, F=4, and M=4) or even "255" (R=3, F=4, and M=4) are that the medical center is losing or has almost lost these customers: they had purchased frequently and spent the most in the past, but for some reason, they have been inactive for some time and have not purchased recently. Lastly, customers in RFM group "111" (R=4, F=0, and M=0) have spent little and purchased only a few times in the past. It has been a long time since they last purchased as well. Customers in this group get less priority because the company has lost these "frugal" customers.

The profile of each cluster is also presented to keep track of the key metrics such as average transaction counts, average length of relationship, average CLV, and recency history. Most customers (44%) are in Cluster #4, a low-spending group, indicating that they are either one-time customers responding to a certain campaign or inactive customers, who once tried a series of treatment programs or different inexpensive promotions and decided not to continue their relationship with the medical center. This lack of interest indicates an ineffective marketing strategy, since the enterprise invested heavily via different marketing channels and promotions to draw potential customers' attention and has already had a chance to impress them when they participated in the program but could not convert them into repeat customers. Based on the historical data from the past three years, customers in this group responded mostly to the Myer's Cocktail campaign, followed by the Colon Hydrotherapy and Liver Detox campaigns. Finally, the lapsing customers in Cluster #1 signal the enterprise that they may start coming back for services, since the average recency is among the lowest compared to the other averages in the other clusters and most of these customers are in the first tier of migration probability. Customers in this group are also among the youngest; thus, any wellness programs such as Colon Hydrotherapy, Myers' Cocktail, ozone therapy, massages and relaxation programs, or weight loss programs might serve them better than the detoxification programs such as chelation therapy or liver detox. Unless the enterprise considers migration, customers in this group might be completely ignored because of their relatively low CLV and infrequent responses to the services.

## 5.3 Limitations

There are some limitations in this dissertation. First, this study collect data from CAM clinic, therefore it may not generalize to the other industry. Second, there are incomplete data since the company does not collect information on any aspects such as blood type, weight, height, or pulse.

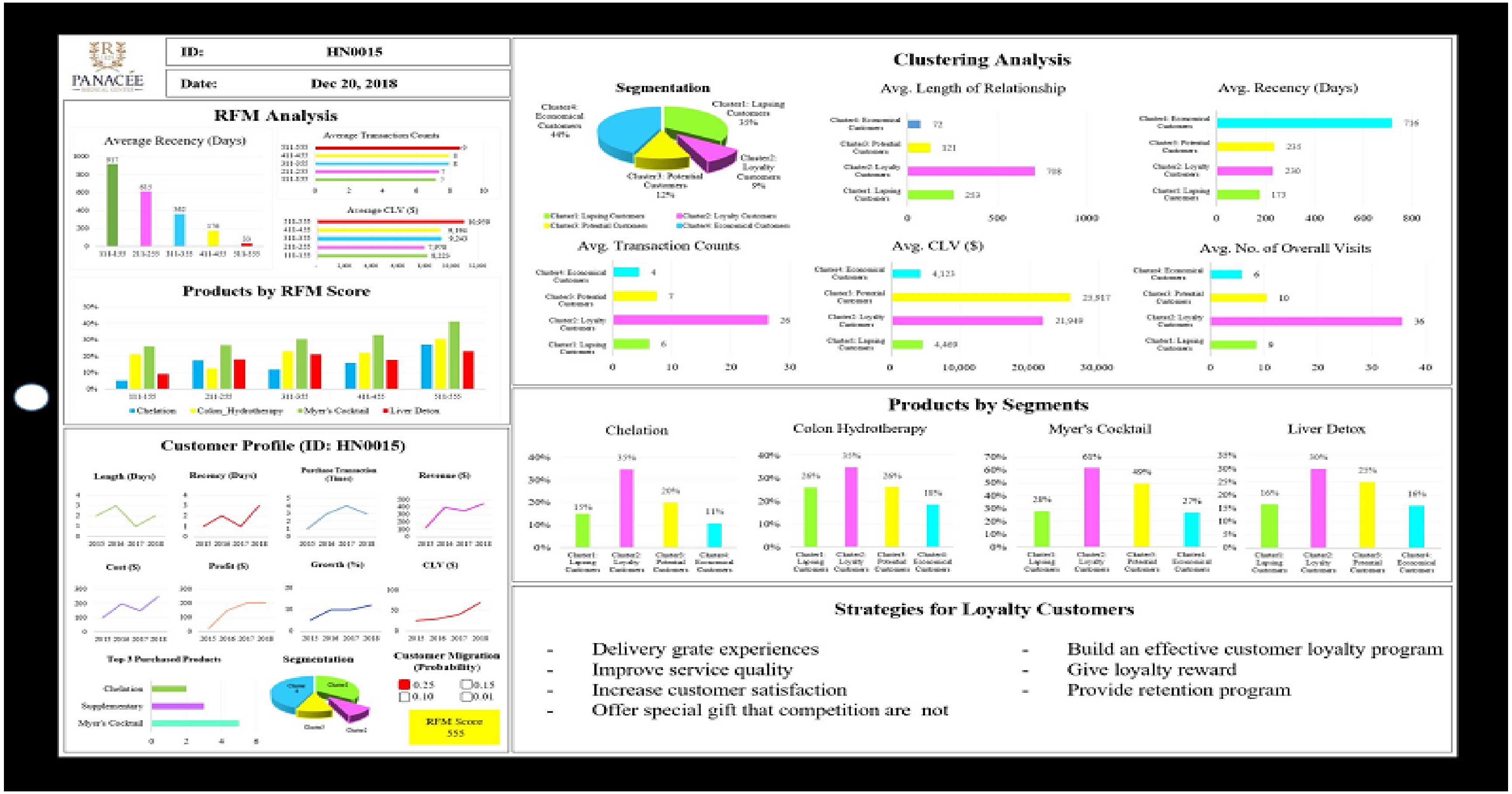



**Figure 5.1** The First Design-Stage of Executive Dashboard (Part I)

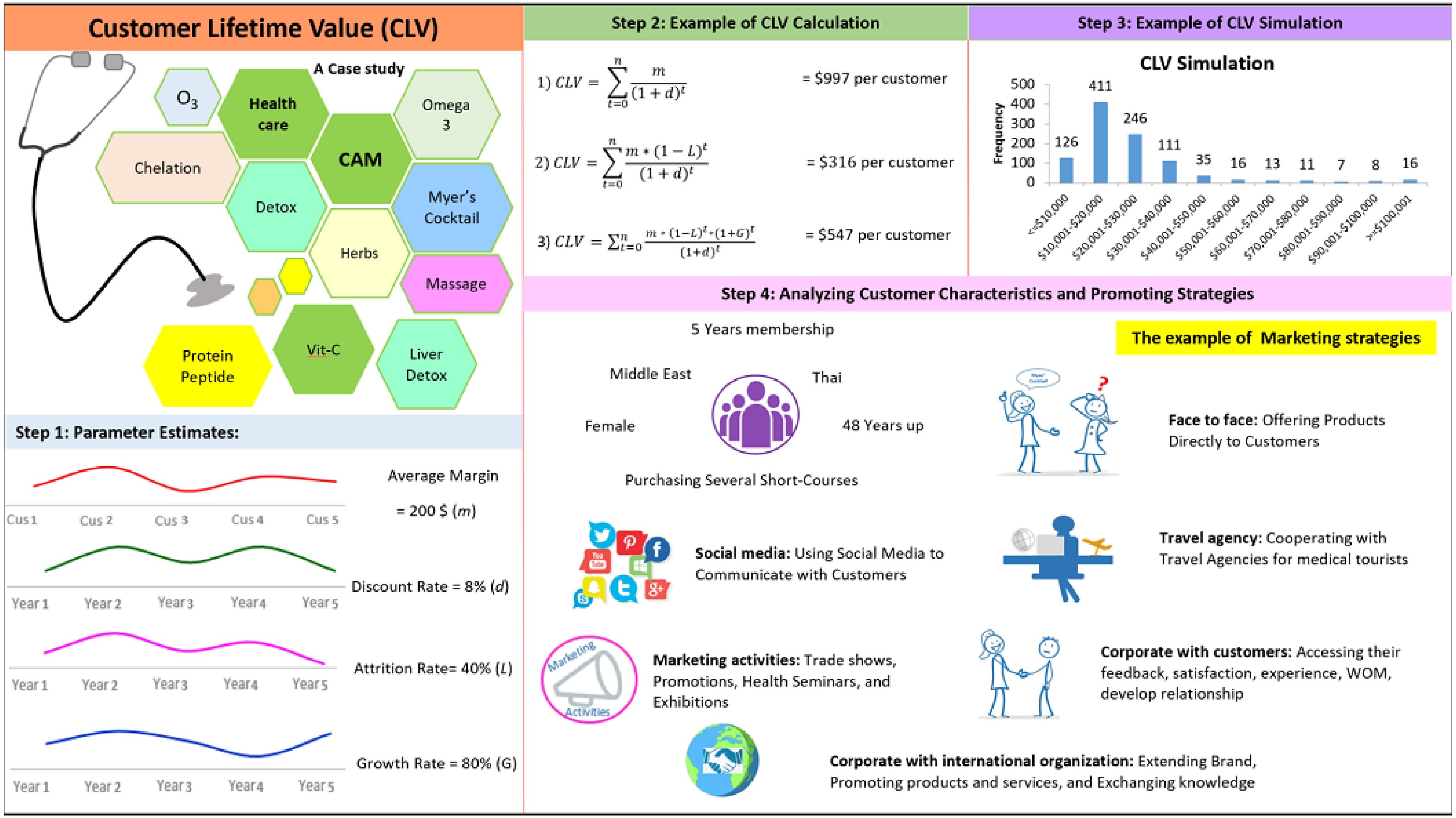



**Figure 5.2** The First Design-Stage of Executive Dashboard (Part II)

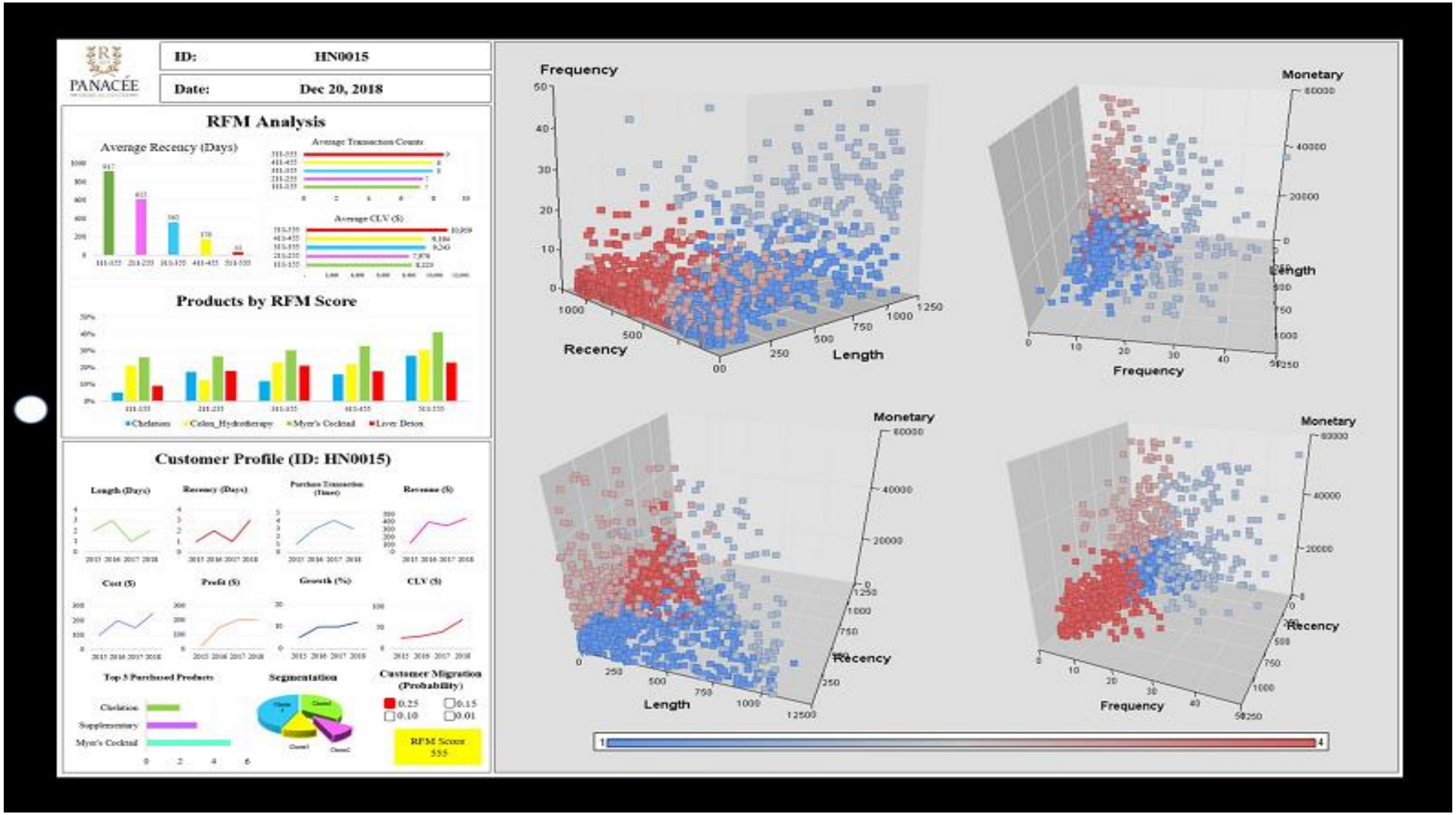



**Figure 5.3** The First Design-Stage of Executive Dashboard (Part III)

# BIBLIOGRAPHY


Anderson, D. R., Sweeney, D. J., Williams, T. A., Camm, J. D., & Cochran, J. J. (2018). *An Introduction to Management Science: Quantitative Approach* (15th ed.). United States: Cengage learning.

Ballestar, M. T., Grau-Carles, P., & Sainz, J. (2018). Customer segmentation in e-commerce: Applications to the cashback business model. *Journal of Business Research*, *88*(1), 407-414.

Barfar, A., Padmanabhan, B., & Hevner, A. (2017). Applying behavioral economics in predictive analytics for B2B churn: Findings from service quality data. *Decision Support Systems, 101*(1), 115-127.

Berger, P. D., & Nasr, N. (1998). Customer lifetime value: Marketing models and applications. *Journal of Interactive Marketing, 12*(1*)*, 17-30.

Berger, P. D., Weinberg, B., & Hanna, R. C. (2003). Customer lifetime value determination and strategic implications for a cruise-ship company. *Database Marketing & Customer Strategy Management, 11*(1), 40-52.

Chang, H., & Tsay, S. F. (2004). Integrating of SOM and K-mean in data mining clustering: an empirical study of CRM and profiability evaluation. *Journal of Information Management, 11*(4), 161-203.

Chang, Chang, C., & Li, Q. (2012). Customer lifetime value: A review. *Social Behavior and Personality, 40*(7), 1057-1064.

Chen, Q., Zhang, M., & Zhao, X. (2017). Analysing customer behaviour in mobile app usage. *Industrial Management & Data Systems, 117*(2), 425-438.

Connrll, J. (2006). Medical tourism: Sea, sun, sand and ...surgery. *Tourism Management, 27*(6), 1093-1100.

Corbin, C. L., Kelley, S. W., & Schwartz, R. W. (2001). Concepts in service marketing for healthcare professionals. *The American Journal of Surgery, 181*(1), 1-7.

Dahana, W. D., Miwa, Y., & Morisada, M. (2019). Linking lifestyle to customer lifetime value: An exploratory study in an online fashion retail market. *Journal of Business Research, 99*(1), 319-331.

Dwyer, F. R. (1997). Customer lifetime valuation to support marketing decision making. *Journal of Direct Marketing, 11*(4), 6-13.

Eiriz, V., & Wilson, D. (2006). Research in relationship marketing: Antecedents, traditions and integration. *European Journal of Marketing, 40*(3/4), 275-291.

Ek Styven, M., Foster, T., & Wallstrom, A. (2017). Impulse buying tendencies among online shoppers in Sweden. *Journal of Research in Interactive Marketing, 11*(4), 416-431.

Estrella-Ramon, A., Sanchez-Perez, M., Swinnen, G., & VanHoof, K. (2017). A model to improve management of banking customers. *Industrial Management & Data Systems, 117*(2), 250-266.

Fader, P. S., Hardie, B. G. S., & Lee, K. L. (2005). RFM and CLV: Using iso-value curves for customer base analysis. *Journal of Marketing Research, 42*(4), 415-430.

Farias, P., Torres, E., & Mora Cortez, R. (2017). A new model for measuring salesperson lifetime value. *Journal of Business & Industrial Marketing, 32*(2), 274-281.

Ferrentino, R., Cuomo, M. T., & Boniello, C. (2016). On the customer lifetime value: A mathematical perspective. *Computational Management Science, 13*(4), 521-539.

Fu, X., Chen, X., Shi, Y.-T., Bose, I., & Cai, S. (2017). User segmentation for retention management in online social games. *Decision Support Systems, 101*(4), 51-68.

Gammack, J. K., & Morley, J. E. (2004). Anti-Aging medicine—the good, the bad, and the ugly. *Clinics in Geriatric Medicine, 20*(2), 157-177.

Glady, N., Baesens, B., & Croux, C. (2009). A modified Pareto/NBD approach for predicting customer lifetime value. *Expert Systems with Applications, 36*(1), 2062-2071.

Gupta, S., Hanssens, D., Hardie, B., Kahn, W., Kumar, V., Lin, N., . . . Sriram, S. (2006). Modeling customer lifetime value. *Journal of Service Research, 9*(2), 139-155.

Gupta, S., & Lehmann, D. R. (2006). Customer lifetime value and firm valuation. *Journal of Relationship Marketing, 5*(2-3), 87-110.

Heper, M. (2013). The cost of creating a new drug now $5 billion, pushing big pharma to change. *Forbes Magazine.* Retrieved from https://www.forbes.com/sites /matthewherper/2013/08/11/how-the-staggering-cost-of-inventing-new-drugs-is-shaping-the-future-of-medicine/#3fde9d513c33

Hu, Y. H., & Yeh, T. W. (2014). Discovering valuable frequent patterns based on RFM analysis without customer identification information. *Knowledge-Based Systems*, *61*(1), 76-88.

Hung, A., Kang, N., Bollom, A., Wolf, J. L., & Lembo, A. (2015). Complementary and alternative medicine use is prevalent among patients with gastrointestinal diseases. *Digestive Diseases and Sciences*, *60*(7), 1883-1888.

Kim, Suh, E., & Hwang, H. (2013). A model for evaluating the effectivemess of CRM using the balanced scorecard. *Journal of integrative Marketing, 17*(2), 5-19.

Kotler, P., & Armstrong, G. (2018). *Principles of marketing.* Lego, Italy: Pearson Education Limited.

Kumar, V. (2010). A customer lifetime value-based approach to marketing in the multichannel, multimedia retailing environment. *Journal of Interactive Marketing, 24*(2), 71-85.

Kumar, V., Ramani, G., & Bohling, T. (2004). Customer lifetime value approaches and best practice applications. *Journal of Interactive Marketing*, *18*(3), 60-72.

Larson, R., & Hostetler, R. (2007). *Precalculus*. Boston, MA: Houghton Mifflin Company.

Lavretsky, H. (2009). Complementary and alternative medicine use for treatment and prevention of late- life mood and cognitive disorders *Aging Health, 1*(5), 61-78.

Marcus, C. (1998). A practical yet meaningful approach to customer segmentation. *Journal of Consumer Marketing, 15*(5), 494-504.

McCarty, J. A., & Hastak, M. (2007). Segmentation approaches in data-mining: A comparison of RFM, CHAID, and logistic regression. *Journal of Business Research, 60*(6), 656-662.

Michel, R., Schnakenburg, I., & von Martens, T. (2017). Effective customer selection for marketing campaigns based on net scores. *Journal of Research in Interactive Marketing, 11*(1), 2-15.

Miglautsch, J. R. (2000). Thoughts on RFM Scoring. *Journal of Database Marketing, 8*(1), 67-72.

Mirzaei, A., Pharm, B., Carter, S. R., & Schneider, C. R. (2018). Marketing activity in the community pharmacy sector - A scoping review. *Research in Social and Administrative Pharmacy, 14*(2), 127-137.

Moreira, P. (2014). Health and medical tourism: Health management and marketing research challenges. *International Journal of Healthcare Management, 7*(4), 221-222.

National Center for Complementary and Alternative Medicine. (2011). *What is complementary and alternativemedicine?* Retrieved 9 Febuary, 2018, from http://nccam.nih.gov/health/whatiscam

National Center for Complementary and Integrative Health. (2016). Complementary, alternative, or integrative health: What's in a name? Retrieved from https://nccih.nih.gov/health/integrative-health

Palmatier, R. W., Dant, R. P., Grewal, D., & Evans, K. R. (2006). Factors influencing the effectiveness of relationship marketing: A meta-analysis. *Journal of Marketing, 70*(4), 136-153.

Peker, S., Kocyigit, A., & Eren, P. E. (2017). LRFMP model for customer segmentation in the grocery retail industry: A case study. *Marketing Intelligence & Planning, 35*(4), 544-559.

Pfeifer, P. E., Haskins, M. E., & Conroy, R. M. (2005). Customer lifetime value, customer profitability, and the treatment of acquisition spending. *Journal of Managerial Issues, 17*(1), 11-25.

Reinartz, W., & Kumar, V. (2000). On the profitability of long-life customers in a noncontractual setting: An empirical investigation and implications for marketing. *Journal of Marketing, 64*(4), 17-35.

Reinartz, W., & Kumar, V. (2002). The mismanagement of customer loyalty. *Harvard Business Review, 80*(7), 4-12.

Ryals, L. (2002). Are your customers worth more than money? *Journal of Retailing and Consumer Services, 9*(5), 241-251.

Safari, F., Safari, N., & Montazer, G. A. (2016). Customer lifetime value determination based on RFM model. *Marketing Intelligence & Planning, 34*(4), 446-461.

Wei, J. T., Lin, S. Y., Chien, W. C., & Wu, H. H. (2012). A case study of applying LRFM model in market segmentation of a children's dental clinic. *Expert Systems with Applications, 39*(5), 5529-5533.

Wilcox, P. A., & Gurau, C. (2003). Business modelling with UML: the implementation of CRM systems for online retailing. *Journal of Retailing and Consumer Services, 10*(3), 181-191.

Wyner, G. A. (1996). Customer profitability: Linking behaviour to economic. *Marketing Research, 8*(2), 36-38.

Zare-Hoseini, Z., Tarokh, M. J., & Nooghabi, H. J. (2011). Lifetime value model in the medical sector: A case study of a restoration and beauty clinic. *International Journal of Pharmaceutical and Healthcare Marketing, 5*(1), 54-66.

# APPENDICES

# APPENDIX A

# APPLICATIONS OF BUSINESS INTELLIGENCE AND MARKETING ANALYTICS IN THE COMPLEMENTARY AND ALTERNATIVE MEDICINE INDUSTRY

## Journal of Information Technology Teaching Case

| | |
|---|---|
| **Journal**: | Journal of Information Technology Teaching Cases |
| **Manuscript ID**: | TTC-20-0004 (Accept (Feb 04, 2020) |
| **Manuscript Type**: | Teaching Case |
| **Keywords**: | Business intelligence and analytics, Marketing Analytics, Price |
| **Abstract**: | This case is designed to illustrate the application of business intelligence and marketing analytics to making proper decisions in a competitor- oriented pricing environment. The case started when Dan, the director of a business analytics consulting firm, was assigned a big project: to help Panacee Medical Center, one of the leading service providers in complementary and alternative medicine (CAM) industry, envisage possible marketing strategies in response to competitors' recent moves that threatened the sales and marketing strategies of its business. The case is divided into three parts. Case A provided an overview of challenges Panacee was facing when one of its competitors, B&C, was about to offer full CAM services with a newly renovated, 5-star, resort- type clinic and high-quality facilities and another competitor, NHC, planned to promote its recent investment in a new laboratory that met international standards at the upcoming Thailand Health & Wellness Expo. Case B focused on insights into customers through different analytical techniques. Case C implicitly outlined possible strategies that might be applicable to Panacee, especially when the services from both B&C and NHC were expected to be priced 5% to 25% below the established market price. Dan needed to decide which direction he needed to propose to Panacee's top management, as the combination of low prices and premium services threatened the medical center and Panacee might lose as much as 30% of its forecast revenue next year. |

# Applications of Business Intelligence and Marketing Analytics in the Complementary and Alternative Medicine Industry


## Abstract

This case is designed to illustrate the application of business intelligence and marketing analytics to making proper decisions in a competitor-oriented pricing environment. The case started when Dan, the director of a business analytics consulting firm, was assigned a big project: to help Panacee Medical Center, one of the leading service providers in complementary and alternative medicine (CAM) industry, envisage possible marketing strategies in response to competitors' recent moves that threatened the sales and marketing strategies of its business. The case is divided into three parts. Case A provided an overview of challenges Panacee was facing when one of its competitors, B&C, was about to offer full CAM services with a newly renovated, 5-star, resort-type clinic and high-quality facilities and another competitor, NHC, planned to promote its recent investment in a new laboratory that met international standards at the upcoming Thailand Health & Wellness Expo. Case B focused on insights into customers through different analytical techniques. Case C implicitly outlined possible strategies that might be applicable to Panacee, especially when the services from both B&C and NHC were expected to be priced 5% to 25% below the established market price. Dan needed to decide which direction he needed to propose to Panacee's top management, as the combination of low prices and premium services threatened the medical center and Panacee might lose as much as 30% of its forecast revenue next year.


**Keywords**: Business Intelligence; Market Analytics; Price War; RFM; Cluster Analysis; CLV

## Case A – The First Meeting

On a busy Monday in October 07, 2019, Dan, the director of a business analytics consulting firm, was assigned a big project to help Panacee Medical Center envisage possible marketing strategies in order to respond to competitors' recent moves that threatened its sales and marketing strategies. Dan was working closely with a newly hired marketing analyst, Ben, who recently received her Ph.D. in Marketing and Data Science at NIDA Business School in Bangkok, Thailand, and Josh, Panacee's experienced marketing manager, to formulate the medical center's options.

Panacee was one of the leaders in medical treatment and detoxification programs, with advanced medical technologies for treatment of various diseases such as Alzheimer's, Parkinson's, diabetes, and hypertension. Last month, however, its main competitor, B&C Beauty and Clinic (B&C) surprised Panacee and the rest of the industry by unveiling new premium treatment therapy services that included a touch of relaxation and superior rehabilitation. In addition, Natural Health Center (NHC), a relative newcomer in the contemporary and alternative medicine (CAM) industry, invested heavily in an advanced laboratory for testing under international standards. Both competitors had seized first place in their own area and received positive feedback from their target markets. More damaging, their services were priced 5% to 25% below the established market prices. The combination of low prices and premium services threatened the medical center, and the marketing team had informed Dan that Panacee might lose as much as 30% of its forecast revenue next year.

The new services from both B&C and NHC had been timed to prevent responses (new investment in laboratory equipment or facilities) before the Thailand Health & Wellness Expo, the industry's most important exhibitions, was scheduled to take place this coming January. Major customers and tourists would be there; thus, Panacee's new marketing campaigns would determine its sales for the rest of next year.

**Current Services**

Panacee Medical Center provided intensive healthcare services with various individualized treatments designed to prevent illnesses and promote good health and long-lasting rejuvenation. Its services could be categorized into three main programs: health checkups, treatment programs, and detoxification programs, along with other special packages such as vitamins & supplements and rejuvenation programs.

- Health Checkups included a variety of services from regular checkups with blood analysis, bio body scans, and a doctor's consultation to advanced laboratory tests such as stem cell counts, hormone tests, heavy metal tests, and gene tests.
- Treatment programs such as ozone therapy, Vitamin C High Dose, intravenous antioxidants, and Myer's Cocktails had recently been in more demand; some had just been marketed and others had been around for a few years and were considered top-notch services in the market.
- Detoxification programs such as chelation, colon hydrotherapy, and liver detox had been well-known in the market since their first introduction in 2014.

Panacee had positioned itself in the sector of complementary and alternative medicine (CAM), which referred to practices that were not part of standard medical care. "Complementary" referred to treatments used together with conventional medicine and "alternative" refers to treatment used in place of conventional medicine. The target markets for Panacee were people or patients seeking alternative treatments or illness prevention along with or instead of conventional medicine. The CAM-related healthcare industry had been attracting a lot of attention nationally and globally over decades.

**B&C**

B&C (Beauty and Clinic) was founded with the aim to provide tailor-made health management for those who wanted to prevent illness while maintaining their healthy lifestyle without medication. B&C had recently revamped its facility to offer a unique approach to healthcare with a boutique feel through its newly renovated resort in a garden oasis located in the heart of Bangkok, Thailand. Its services covered a variety of treatments and care such as 1) massage and aromatherapy for muscular symptoms and bone structure, 2) a proionic system that had the ability to rejuvenate inflamed cells in order to relieve chronic muscle pain and strain and office syndrome, 3) radiance facial massage and treatment, and 4) colon detox using reverse osmosis water to detoxify the colon by removing toxins which had accumulated in the deep intestine. At the Thailand Health & Wellness Expo, it was believed that B&C would promote its new high-quality and full- service facility: a 5-star-resort-type clinic with environmentally friendly accommodations where customers could relax and maintain their health of body and mind while participating in the healthcare program. The promotional packages were expected to be discounted about 5% to 25%, as were B&C's offers last year at the expo.

**NHC**

NHC (Natural Health Center) had emerged as one of the top health centers for its recent large investment in an Australian-standard-licensed laboratory. The new laboratory allowed fast and accurate consultations and pathology testing including full blood examinations for C Reactive Protein, Erythrocytes Sedimentation Rate, B12, Iron, Zinc, Vitamin D3, Homocysteine, etc. Its famous treatment program was an energy cocktail, aimed at potentially reducing chronic fatigue or the effects of chronic fatigue syndrome. The ingredients for the energy cocktails, which included Vitamins C and B, magnesium sulfate, magnesium chloride, and an electrolyte solution, could be customized to induce fast-acting sustained energy, especially when patients needed rest or felt tired or exhausted. It was believed that at the Thailand Health & Wellness Expo, NHC would promote its new investment in the internationalized standard laboratory for on-site consultations so that suitable treatments such as its customized energy cocktail ingredients could be prescribed. Additionally, it was expected that the promotion at the Expo would be priced at about 10% to 20% below what Panacee was offering right now.

**Current Strategies at Thailand Health & Wellness Expo "Price War"**

In the last meeting with his management team, Dan was informed by Josh about the campaigns both B&C and NHC were expected to launch at the expo this coming January.

> Josh: We had about two months to prepare for the booth and campaigns at the expo. This time, our biggest competitors had shifted their strategies from fragmented care to an integrated healthcare model, since more discerning customers were demanding faster, more convenient, and more affordable personalized services.

NHC advertised its fast health checkup packages with accurate, same-day labs results where, in the past, the lab tests lasted almost all day. The client met with a doctor later in the day for a consultation, but the lab results might be delivered the next day. B&C's strength was its one-stop healthcare service, with the most modern, comfortable, convenient, and comprehensive services and facilities in the relaxing atmosphere of a spa and a 5-star hotel. Their current websites had started advertising the events, their booths, and some promotions. Based on the contents we saw in the banners and brochures and the comments from the blogs in Facebook, the competition at the expo seemed very intense this year compared to last year.

> Josh: In this industry, price wars were inevitable. Since our new treatment packages would be targeted and launched at the Thailand Healthcare+ Expo in June next year, the current strategies for the Thailand Health & Wellness Expo this coming January would just be customized packages based on purchasing history. Additionally, prices would likely be slashed (roughly 20%) to match or beat both B&C and NHC.

**The Initial Decision Making**

Dan had been thinking about this issue, which normally happened when competitors had lowered their prices and the company were concerned about sales and revenue. However, a hasty decision to reduce its price to match competitors, or basically to respond to a price war, might impact the long-term marketing strategies and did more harm than good. Dan turned the issue over to Ben and asked her whether price-war strategies should be implemented at the Thailand Health & Wellness Expo. Of course, it would be tough to launch any new products and services at this time, and price always became a much large factor in purchasing decisions. As a newly hired marketing analyst, Ben had to decide whether going toward the discounted treatment packages to compete with B&C and NHC was the right direction as Josh suggested. She spent a night thinking about the pros and cons of such a decision before meeting with Dan. As a marketing analyst, how should she plan for the analysis for the meeting tomorrow?

## Case B – More Insight into Customers

**Nutrients and Ozone Therapies and Detoxification Programs**

During the meeting the next day (Oct 08, 2019), Dan emphasized that many aspects needed to be considered before Panacee decided to either respond to the competitors' strategies or ignore them and focused on Panacee's strengths. Ben agreed with Dan and asked Josh about the promotional treatment packages the company planned to highlight at the Thailand Health & Wellness Expo. Josh quickly responded:

> Our 1st and most famous flagship program was detoxification packages, which aimed to remove toxins from the human body. The packages included a series of chelation therapy and colon hydrotherapy treatments. Chelation therapy rid the body of heavy metals, for example, arsenic, cadmium, lead, and mercury, while colon hydrotherapy or colon cleansing was a treatment to clean the colon through the administration of water, herbal solutions, enzymes, or other substances such as coffee.
>
> The 2nd treatment packages, recently added to our line pf products based on market trends, were a Myers' cocktail and ozone therapy. A Myers' Cocktail treated a wide range of diseases and symptoms such as asthma, migraines, tiredness and stiffness, and allergies by using an infusion of mixed vitamins, and ozone therapy increased the amount of oxygen in the body through the introduction of ozone. The marketing team were about to advertise these two programs on its social media and website and, later, persuaded its loyalty and potential customers to come to the booth at the Expo.
>
> Dan asked the team, " Would lowering our prices, especially on our premium services, hurt Panacee's credibility, brand image, and margin more than it would help?... This issue was very challenging and needed a bit more thought.

From experience, Dan believed that competitors dropped their prices for two main reasons: excess stock and market share. However, in the CAM industry, excess inventory should not be the big issue. Thus, the most common reason to go in this direction was to increase their market share. However, Dan still asked Ben to find out why the competitors dropped their prices. What drove such a decision to engage in this price war? Would B&C's and NHC's strategies really hurt Panacee?

**Market Share**

Dan believed that to evaluate how well Panacee was doing in relation to B&C, NHC, and the rest of the industry as a whole, it was important to first evaluate market share domestically for Panacee's main services. Focusing only on the revenue trend and the size of the CAM market might not be enough. Ben quickly pulled the market information and informed Dan that Panacee currently held approximately 30% market share for the detoxification programs, followed by B&C (10%), and NHC (3%) but only 5% for nutrients and ozone therapies; B&C was the leader at 35% and NHC was second at 15%. Dan was still in doubt as to whether competitively lowering Panacee's prices and increasing advertising to grow market share were the right decision.

**Product Life Cycle**

Another factor that could not be ignored was product life cycle, as it described a number of commercialization steps that Panacee went through as it penetrated the healthcare market: initial research, sales growth, maturing of the healthcare demand, and the decline of the services. Ben found that healthcare technology innovation was strongly influenced by life cycle effects, which was associated with price erosion. The complementary and alternative medicine industry continued to see an increased number and type of services or products (such as massage and therapy, acupuncture, dietary supplements, herbs, detoxification, and nutritional therapy) being introduced in today's highly competitive healthcare market. Thus, in order to compete effectively, CAM service providers must be able to respond quickly to the unique demands. Josh added that he had seen the need for these providers, including Panacee, B&C, and NHC, to be more agile and innovative in order to create a broad range of new offers to respond quickly to the market. Based on the healthcare market trends in term of market size and market share, he could assure Dan and Ben that CAM was still in the growth phase. The trends for both nutrients and ozone therapies and detoxification programs were increasing and were positively correlated with the rise of the healthy living and wellness trend.

**Cost of Services**

Dan also asked Ben to dig deeper into all expenses incurred in providing the healthcare services required for both programs. Hopefully, Josh would be able to considerably lower Panacee's overall cost of services if he decided to offer the discounted packages to ensure that profits remained the same. While preparing for the report, Ben had to allocate both direct and indirect resources related to each service. The average cost of services had spiked to approximately 65% and 55% of sales on the detoxification programs and the nutrients and ozone therapies respectively, driving a significant decrease in gross profits. This change had been driven by higher expenses from recent investment in exclusive amenities and equipment.

> Dan could foresee that reducing the prices of packages to match competitors' reduced-price packages would definitely impact Panacee's profit in the long run. In other words, cutting prices meant cutting profit margins. Josh immediately asked a relevant question: "Or should we take the high road and slowly watch B&C and NHC steal our customers?"

Although the question from Josh sounded reasonable, Dan asked the team how Panacee should respond if the competitors promptly cut prices again. Would that lead to a worse situation? Both Dan and Ben had to get more insight into Panacee's customers before recommending solutions to the top management of the medical center.

**RFM Analysis**

Ben proposed that the easiest way to understand Panacee's customers was to start with RFM analysis, a segmentation technique based on three attributes: recency, frequency, and monetary value. Recency (R) of the last purchase referred to how long it had been since a customer purchased a product or service from the company. The shorter the time, the lower the (R). Frequency (F) referred to how often a customer had placed orders with the company within a particular period. The higher the number of transactions, the bigger the (F). The monetary value (M) of the purchases referred to the amount a customer had spent within a particular period. The higher the amount spent, the bigger the (M).

> Dan emphasized that this RFM model would at least give top management a great deal of valuable information to better understand its customers, especially how customers had responded to both nutrients and ozone therapies and detoxification campaigns.

Appendix A1 presented an example of customer ID 10001, who last visited Panacee Medical Center for an ozone therapy treatment about four weeks ago (Recency). In the past 2 years, he purchased a total of 6 treatment programs (Frequency), spending a total of $680. Ben pointed out that customers in the nutrients and ozone treatment group were considered big spenders (at approximately $892 on average), since they spent the most compared to customers in the detoxification programs, where the average monetary value was estimated at $430 on average. However, customers in the detoxification program seemed to be more loyal, since they frequently purchased the packages as opposed to those in the nutrients and ozone group (22 vs. 6 transaction counts). The average recency for both groups were about the same.

Ben also illustrated a simplified segmentation model in a quadratic form that included all marketing campaigns, not just nutrients and ozone therapies and detoxification programs, with an average frequency of purchases of 10 orders and an average of total amount of purchases of $700 (see Appendix A2). Group #1 customers were considered loyalty customers, as they purchased treatments quite often, with more than 10 transaction counts, but a total amount spent of less than $700. Customers in Group #2 were a lower priority to Panacee since they had spent less and purchased less frequently compared to the other groups. Customers in Group #4 were big spenders. This RFM analysis caught Dan’s attention because the goal of Panacee was to encourage the customers who had bought most recently and most often and had spent the most. Thus, ideally, customers in Group #3, who had been very active and spent the most, were considered the most valuable to Panacee. As presented in Appendix A2, “detoxification” customers and “nutrients and ozone therapies” customers were segmented in Group #1 and Group #4, respectively.

**Customer Lifetime Value**

Additionally, Dan and Ben agreed that another factor to be taken into account when considering the value Panacee placed on its customers was customer lifetime value.

> Josh looked at the historical data for customers in Groups #1 and #4 and informed Dan that each year, Panacee had lost approximately 10% and 40% of its customers, also called the attrition rate, for the detoxification programs and the nutrients and ozone therapies, respectively. However, the customers who were still loyal to the medical center usually increased the number of detoxification program purchases by approximately 5% and the number of nutrients and ozone therapy purchases by 25%. Considering the discount rate of 8% annually, Dan decided to calculate the average customer lifetime value (CLV) for customers in both groups as the reference point (see Appendix A3).

**Cluster Analysis**

After integrating the attributes from RFM and CLV, Ben added that cluster analysis could also help top management better capture the nature of Panacee’s customers that shared common characteristics. Ben also modified the cluster analysis by replacing the monetary (M) parameter with CLV in order to focus on the future lifetime value of Panacee’s customers rather than just a snapshot of how much they had spent since their first purchase. Appendix A4 presented the profile of each cluster for all customers considering recency, frequency, CLV, and length of relationship, which referred to the number of days from the first to the last visit.

> From the profile of customers in Cluster #1, Ben believed that they were Panacee's loyalty customers, as they were long-time customers with the highest average length of relationship, high transaction counts, and relatively high customer lifetime value. She considered customers in Cluster #2 potential customers since they were relatively new to the medical center (lower- than-average length of relationship). Although they had not purchased a lot of treatment programs, they were among the highest-value customers.

The length of relationship and the cluster profiles confirmed that customers responding to the detoxification program were segmented in Cluster #1 and those responding to nutrients and ozone therapies were segmented in Cluster #2.

> Dan immediately asked Josh to check whether significant number of customers purchased both detoxification programs and nutrients and ozone therapies, since they were segmented in different target market groups. Josh confirmed that the number of overlapping customers was minimal. However, Ben argued that those overlapping customers were long-time customers with higher-than-the-average CLV values.

**Decision Choices**

After receiving more valuable information about the customers with regard to market share, cost of services, RFM analysis, customer lifetime value, and cluster analysis for customers in both nutrients and ozone therapies and detoxification programs, both Dan and Ben had to prepare an executive report to present to top management at Panacee in the next meeting. The report must include what options were available for Panacee to respond to the strategies the marketing team expected B&C and NHC were about to offer at the Thailand Health & Wellness Expo in about two months and in which direction it was reasonable for Josh to proceed.

## Case C – Final Verdict

### Marketing Channel Analysis

While preparing the final report to present at the first executive meeting with top management of Panacee, which was scheduled on Oct 30, 2019, Dan seek one more opportunity to gather more information about marketing channels in the past several years. Ben asked Josh about Panacee's customer acquisition from various channels for customers who were still active with Panacee.

> Josh reported that over the past two years, approximately 54% of Panacee's new customers had come from word-of-mouth and recommendations from executives, agents had recruited about 23.89%, and promotional campaigns with a well-known bank had brought in 14.63% (Appendix A5(1)).

Participating in exhibitions such as the Thailand Health & Wellness Expo and Thailand Healthcare+ Expo was a marketing strategy that had instrumental in Panacee's promotion of a variety of services, in sharing updated information about its services, and in establishing relationships or negotiating deals with its loyalty customers as well as potential customers.

> Josh added that, recently, customers acquired through the exhibition channel had been mostly one-time customers; less than 2% had become loyalty members at the medical center. This low percentage might be a good indicator that this channel was not as effective as it was 3 to 5 years ago.
>
> Ben, however, argued that customers acquired from the expos who became loyalty customers had, on average, relatively high transaction counts (Appendix A5(2)) and a high average monetary value (Appendix A5(3)). In fact, most of them were in the detoxification programs.

Dan believed that both Josh and Ben had a valid point. The bigger question was not competing in the price war with its competitors but whether Panacee should still invest heavily in the expo. He understood that Josh had a lot of pressures and challenges every year, as the events had experienced decreased attendance and the physical size of the booth space in net square feet had declined as well. Josh had worked very hard to attract customers and had put a lot of effort into the marketing and promotion strategies for the expo. Because of these high levels of investment for participating in the expo, even though Panacee participated in only these two big events per year, top management was demanding higher levels of justification for its involvement and expected a significant return on its expo investment.

> Josh provided another piece of bad news: what Panacee invested in the Thailand Healthcare+ Expo in June this year had not yet been recovered. But as the decision to participate in the Thailand Health & Wellness Expo this coming January was already made at the beginning of the fiscal year, he had to move forward with this strategy.

Having listened to what Josh had been reporting—that most customers acquired from the expo in the past few years had been rarely continued to purchase services—Dan did indeed understand Josh's frustration.

**Revisiting its Target Market**

Ben also furthered analyzed those one-time customers and found that...

> Most of them were health tourists or medical tourists who, spurred on by low-cost flights, traveled to Thailand to address their health or medical needs. This had been a massively growing trend in Thailand since the government campaign, 'Thailand — AEC Healthcare Tourism Hub'; these tourists were looking for world-class medical facilities, bewitching beauty and hospitality, a service-driven culture, and a high standard of healthcare.
>
> Additionally, 90% of them were Myer's cocktails' customers.

Dan still saw a lot of potential in participating in the expo. The expo was an effective and efficient marketing venue for enhancing communication and face-to-face interaction with loyalty and potential customers. The value of the loyalty customers from the expo was higher than the value of those acquired from Panacee's partners or the bank. The one-time customers were definitely in different target groups. Dan needed to confirm with top management the target segments for both the detoxification program and the nutrients and ozone therapies and whether discounted-price packages really would impact the sales performance.

**More Insight from the Segmentation Profiles**

Dan suggested that using predictive models for an in-depth analysis of the behavior of customers who were loyal to the medical center might give us more insight into customers. In other words, it was important to identify how its existing customers were likely to respond to any Panacee's treatment campaigns in the future utilizing the same data gathered for RFM, cluster analysis, and market channel analysis. A quick logistic regression analysis (Appendix A6) and a neural network model (Appendix A7) were developed.

> Ben surmised that customers in the detoxification programs were middle-aged. Most of them had been with Panacee for a long time. The most effective marketing channels for this detoxification segment were through agents, call centers, and corporate seminars.
>
> Interestingly, customers in this group rarely responded to the promotional campaigns for a free treatment.
>
> Josh also interpreted the results of the logistic regression model: customers in the nutrition and ozone segment seemed to be the opposite of those in the detoxification segment: older and relatively new customers contacted through social media channels and word-of-mouth recommendations. Customers in this group utilized the promotional campaigns for a free treatment before actually purchasing the treatment courses.

The results from applying these two models to relatively new customers in both programs, those who had been active in the past six months showed that customers in the detoxification program, on average, had a better chance of purchasing treatment courses than those in the nutrition and ozone therapy (68% vs. 43%). The results seemed reasonable considering what we observed from both RFM and cluster analysis.

**Price vs. Perceived Value**

It was important for top management to market its services beyond price: to position itself in the eyes of its customers based on the value of services and to move away from the concept of affordability. Having valuable treatment programs was one thing but having the ability to sell value was what would set Panacee apart in a sea of price-competitive services.

> Dan expected that at the meeting with Panacee's top management, one of the top executives would say, 'Yes, both B&C and NHC had lower prices. But so what? Panacee had a better brand, more experience, services, a loyalty community, and the list could go on and on. We just had to ensure that we communicated well enough about all the incredible services we had. Position ourselves as the high-quality option and make them an "apples to oranges" comparison rather than trying to be "apples" like our competitors.'

Taking the Myer's Cocktail customers as an example, Panacee should adjust the nutrient mixture to match specific diseases and symptoms. The blend of vitamins, minerals, and nutrients should be reformulated in the right proportions to what customers needed, from boosting the immune systems, reducing fatigue, or treating chronic conditions to resolving digestion issues, combating chronic exhaustion, energizing the body, or fighting infection. If treatment programs were limited because of the lack of investment in technology or resources, finding new customer segments and improving customer services and experience should be effective ways to one-up B&C and NHC, despite any discounted packages they introduced at the expo.

On the other hand, lowering the price of Panacee's treatment programs in a bid to win extra market share was worth consideration.

> Josh added that cutting prices was understandable when Panacee's competitors decided to make an aggressive move by undercutting prices on its value-added services, for instance, the case of newly innovated facilities for B&C and the investment in a new laboratory for NHC, after a period pf relative price stability in the CAM industry. Additionally, since the average cost of services had been gradually increasing for a few years, lowering Panacee's prices a bit to gain a little extra from its customers might generate improved cash-flow and consequently help us recover what we had invested.

Dan agreed that what Josh was mentioning should not be ignored, especially in this tough economic time. Price was always an important factor in purchasing decisions.

> Ben offered another view: that lower prices might work well in some situations. For instance, Panacee's detoxification programs were the leader in the market considering both market size and market share. Offering a small bundle of packages such as a free health checkup with a special price for detoxification packages could, in the extreme case, drive Panacee's competitors out of business, or customers would at least be willing to switch for the value they would receive from such a promotion. Another example was that since the nutrients and ozone therapies were relatively new in the market, penetration pricing for these programs into an already highly established market as well to gain market share might be a good option for a short-term strategy.

**Price Discrimination**

The last angle that Dan wanted to discuss with the team was a price discrimination strategy where Panacee could charge different prices to different segments for the same services for reasons not associated with the cost of the services. One of the ideas for such a practice was to price the same services differently based on the volume of services purchased or the demand quantity for each group of customers.

> To ensure that the team members were all moving in the same direction, Josh clarified with Dan that, instead of offering a discounted price for each treatment program, Panacee could offer a special promotion discount of 10%, for instance, when customers purchased both a detoxification program and nutrients and ozone therapies together; offer campaigns like "Buy 10 treatment courses, Get a 10% discount or 2 additional treatments for free"; provide special discounts for foreign customers, etc.

The examples Josh provided exactly illustrated the purpose of price discrimination, which was to capture the market's consumer surplus by maximizing the prices that Panacee's customers were willing to pay, by offering special prices for services according to the quantity demanded, and by offering discounts to members of certain groups. This pricing strategy might potentially give Panacee the opportunity to expand the market by selling to a group that might not buy otherwise.

**Business Intelligence Dashboard**

At this point, Dan believed that the team had gathered enough relevant information on indicators for measuring Panacee's marketing strategies to compete with both B&C and NHC. The next step was to prepare a business intelligence dashboard to aid in this type of decision making. Dan explained further to Josh and Ben the importance of business intelligence, which was nothing but a system that combines architectures, databases, analytical tools, and applications to enable business associates at all levels of an organization to view, access, and analyze data for better business decisions.

*Database Management Layer*

Dan added that database management was the foundation of BI, which consisted of a repository of current and historical data collected to support decision making. As Josh had been involved with Panacee's enterprise data warehouse for several years, he thought that the data retrieved for RFM analysis, CLV estimation, cost of services, and cluster analysis was well organized. However, Ben, who was responsible for most of the analytical parts, raised the important aspect of the challenges of the data preparation process. Although all data were easily accessible and retrievable, she had spent about 70% of her project time on cleaning up the data to make it ready for analysis in the different scenarios. Ben also noted that the data were retrieved and integrated from multiple sources (demographic information, transaction-based data, marketing channels, health-related information, customer activities, and course therapies). Dan reminded Ben not to forget to explain to the top management how data were collected, organized, stored, extracted, and integrated.

*Business Performance Management (BPM) Layer*

Dan insisted that at the next executive meeting, it would be very important to show top management that all decision choices were linked to the organization's strategies. BPM comprised a set of performance management measures that helped top management translate its strategies and objectives into actionable plans. Dan again asked Ben to clearly provide the definitions of all key performance metrics such as sales, revenue, costs, profits, CLV, STP (Segment, Target, Positioning), customer retention rate, and probability of returning for future campaigns. These metrics provide the direction for what factors need to be evaluated, analyzed, and monitored.

*Business Analytics Layer*

Business analytics usually referred to the broad use of quantitative methods and statistical analysis to discover new insights from the data by drilling down to the details of the data, to understand business performance, or to achieve desired outcomes. For Ben and Josh, a lot of techniques had been used to analyze data from customers in both treatment programs to understand their values, to classify them into subgroups which shared similar characteristics, or to build more complex mathematical models, such as logistic regression or neural network models, which are considered machine learning-based techniques as a part of Artificial Intelligence (AI) and were used to predict the possibility that customers would return in the future.

*User Interface Layer*

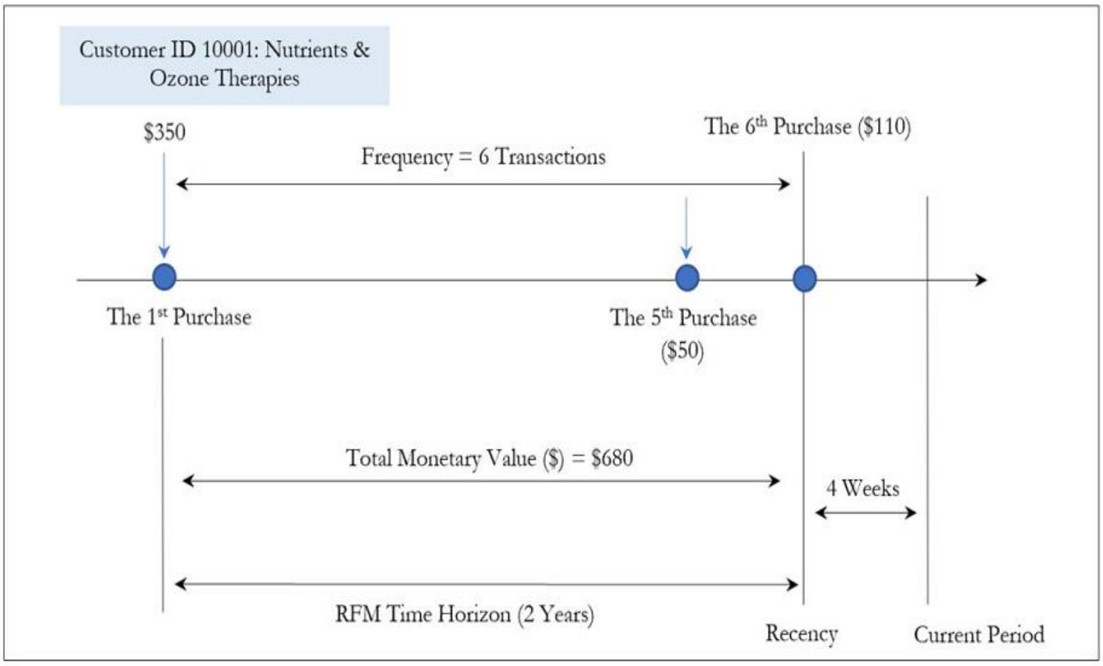
Dan explained further the importance of the user interface layer, which could be in the form of a dashboard or a graphical interface developed to provide a comprehensive visual view of data and information. The dashboard Ben developed (Appendix A8) was a good example: it was designed to track all key performance metrics and to link the data management, business analytics, and business performance management layers, and it allows the top management of Panacee to interact with the systems.

**Time to Propose the Final Recommendations**

Based on what Dan had learned in the meeting with Josh and Ben, he knew that dealing with the competition-oriented pricing situation was inevitable: B&C and NHC might try to increase their market share by attracting Panacee's customers or other potential customers through price lowering. His original idea was about "surviving a price war, rather than trying to win it," standing by the premium pricing. He thought it was fine if Panacee might lose customers who wanted cheaper services, but the focus should be on those who cared more about value. Dan also believed that, of course, there would always be a place for a low-cost leader but that Panacee should respond to price challenges intelligently. However, Josh's opinions and the results from Ben's analysis made him hesitate a bit. After receiving more insights about Panacee's customers through CLV, RFM, cluster analysis, and marketing channel analysis, Dan now needed to decide which direction he needed to propose to the top management. This was quite challenging, as the Thailand Health & Wellness Expo would start in about two months and it would be difficult for Panacee to renovate its facilities or rush the R&D team to offer a new product at the expo.

**Discussion:**

1. Discuss the pros and cons of a price war
2. Please list all factors that should be considered in analyzing nutrients and ozone therapies and detoxification campaigns for the upcoming expo.
3. Calculate the customer lifetime value (CLV) for customers in the detoxification segments when the growth rate is estimated a little higher, to 10%, if Panacee combines the detoxification packages with ozone therapy. However, the chance of losing customers to B&C could be up to 30% as well when B&C offers discounted detoxification packages at the Thailand Health & Wellness Expo. The discount rate remains the same at 8%.
4. Please construct the business intelligence architecture for this competition-oriented pricing decision and identify the components and their interrelated functions.
5. Discuss further how AI (deep learning and machine learning) can be used to enhance marketing analytics, especially in such competition-oriented pricing situations.
6. Discuss the possible options for dealing with the B&C and NHC strategies and make a final decision as to which direction Dan should recommend to the top management at Panacee.




| Program | Average Recency (R), Week | Average Frequency (F), Counts | Average Monetary Value (M), $ |
|---|---|---|---|
| Customers: Nutrients & Ozone Therapies | 4.5 | 6 | $892 |
| Customers: Detoxification Program | 3.8 | 22 | $430 |

**Figure Appendix A1** RFM Analysis

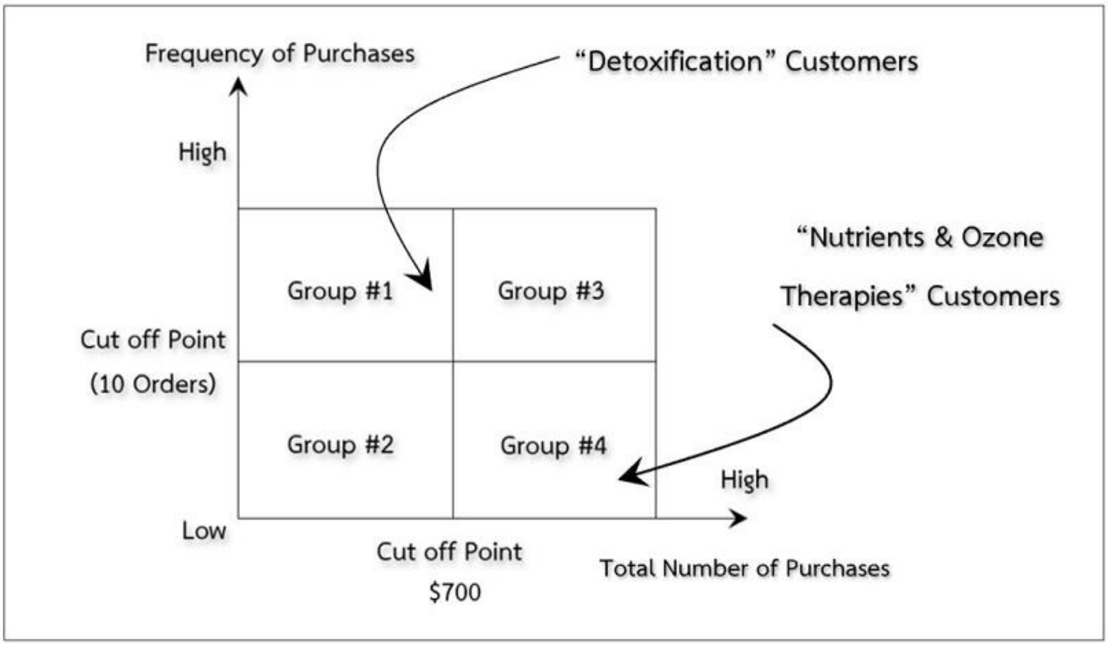



**Figure Appendix A2** The Quadratic Form of Frequency and Monetary Coding

$$CLV_{avg.} = Rev_{(1^{st}\,Year)} + \frac{Rev_{(2^{nd}\,Year)} * Growth\ Rate * Attrition\ Rate}{Discount\ Rate} + \frac{{Revenue_{(3^{rd}\,Year)}}^{2} * Growth\ Rate^{2} * Attrition\ Rate^{2}}{Discount\ Rate^{2}} + \frac{{Revenue_{(4^{th}\,Year)}}^{3} * Growth\ Rate^{3} * Attrition\ Rate^{3}}{Discount\ Rate^{3}} + \cdots + \alpha$$

$$CLV_{avg.} = \frac{\text{Average Revenue/Year}}{Discount\ Rate + Attrition\ Rate - Growth\ Rate}$$

When the average total spending of all customers in the detoxification programs was \$430, the discount rate was 8%, the attrition rate was 10%, and the growth rate was 5%, CLV was

$$CLV_{avg.} = \$430 + \frac{\$430 * 1.05 * 0.9}{1.08} + \frac{\$430^{2} * 1.05^{2} * 0.9^{2}}{1.08^{2}} + \frac{\$430^{3} * 1.05^{3} * 0.9^{3}}{1.08^{3}} + \cdots + \alpha$$

$$CLV_{avg.} = \frac{\$430}{0.08 + 0.1 - 0.05} \approx \$3{,}308$$

When the average total spending of all customers in the nutrients and ozone therapies was \$892, the discount rate was 8%, the attrition rate was 40%, and the growth rate was 25%, CLV was

$$CLV_{avg.} = \$892 + \frac{\$892 * 1.25 * 0.6}{1.08} + \frac{\$892^{2} * 1.25^{2} * 0.6^{2}}{1.08^{2}} + \frac{\$892^{3} * 1.25^{3} * 0.6^{3}}{1.08^{3}} + \cdots + \alpha$$

$$CLV_{avg.} = \frac{\$892}{0.08 + 0.4 - 0.25} \approx \$3{,}878$$

**Figure Appendix A3** Customer Lifetime Value

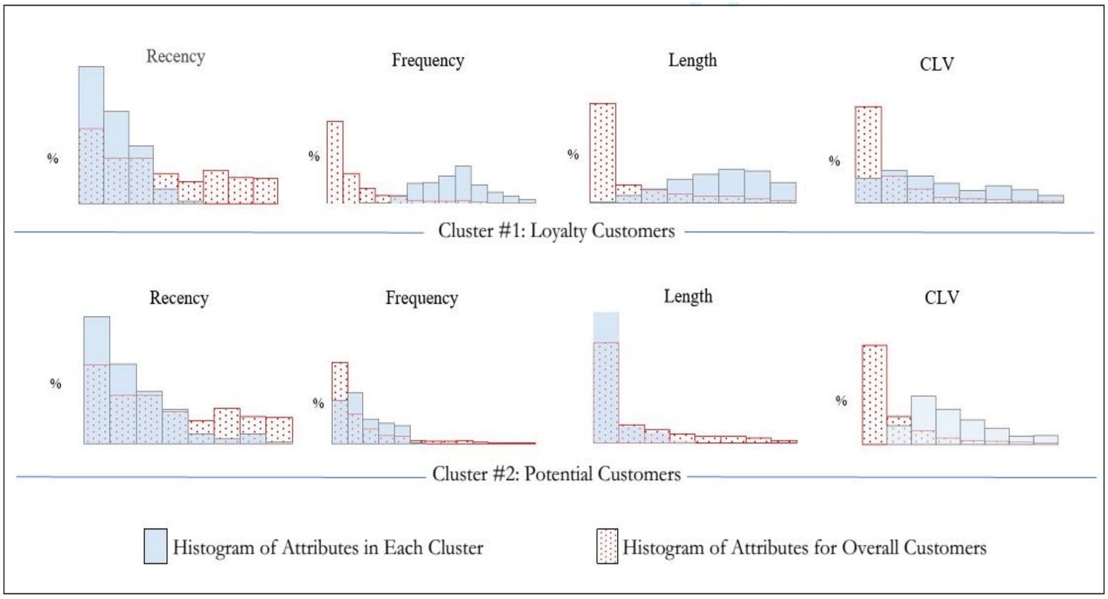



**Figure Appendix A4** Cluster Analysis

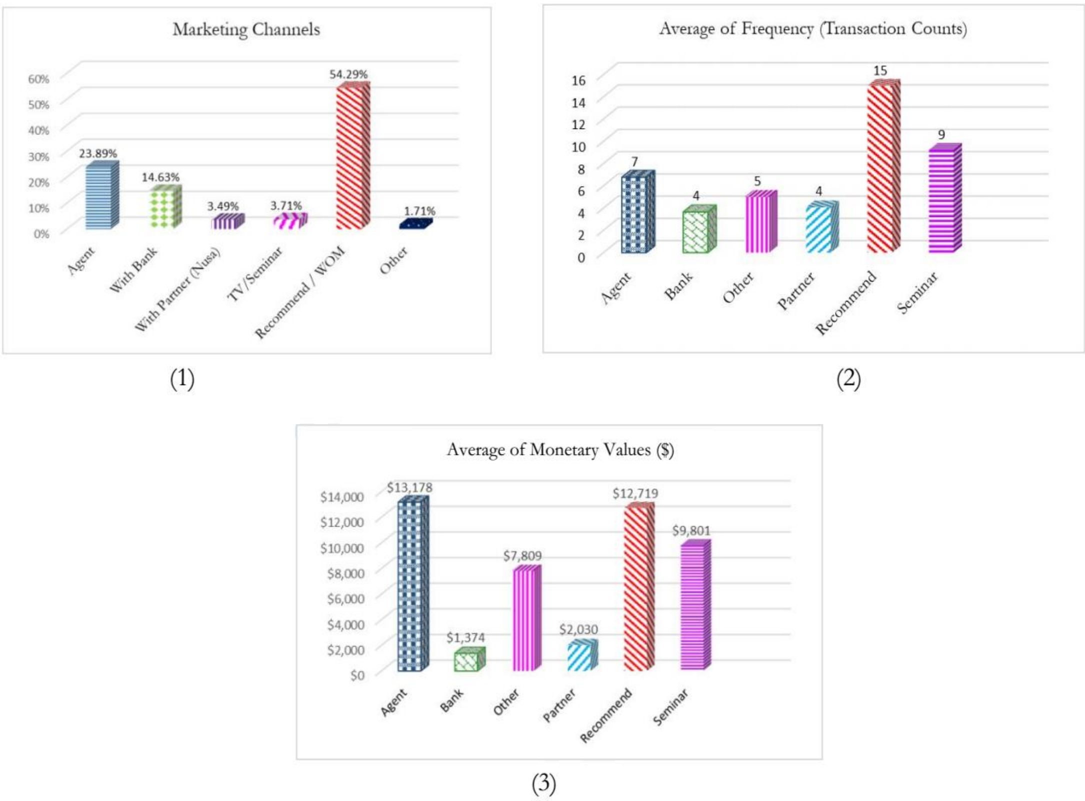



**Figure Appendix A5** Marketing Channel Analysis

**For Detoxification Segment**

Logit (Y=1) = – 0.9929 – 0.00687 (Age) + 0.0193 (Frequency of Visits) + 0.000248 (Length of Relationship) + 3.933E-6 (Total Spend) + 0.1928 (Agent) + 1.0172 (Call-In) – 1.0311 (Social Media) + 0.5664 (Seminar) – 0.0247 (Recommender) – 0.0989 (Free Promotion) + …..

**For Nutrition and Ozone Segment**

Logit (Y=1) = 0.00298 + 0.00496 (Age) + 0.0745 (Frequency of Visits) – 0.00053 (Length of Relationship) + 0.000088 (Total Spend) – 0.4423 (Agent) – 0.3067 (Call-In) + 0.4049 (Social Media) – 0.6219 (Seminar) + 0.5364 (Recommender) + 0.8264 (Free Promotion) + …..

**Figure Appendix A6** Logistic Regression

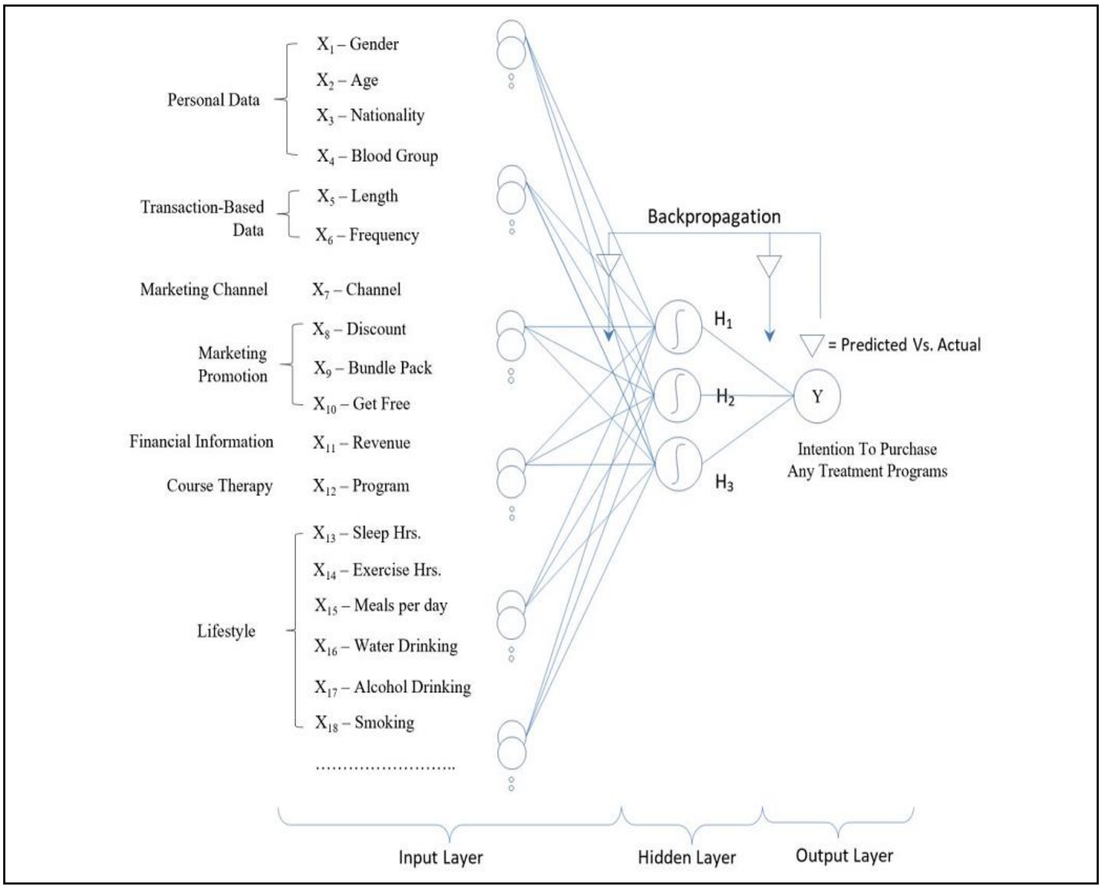



**Figure Appendix A7** Neural Network Model

**For Detoxification Segment**

Logit (Y=1) = -1.8348 – 1.6951 $H_1$ - 1.0351$H_2$ + 1.2053 $H_3$

$H_1$ = tanh (-7.8862 – 1.0150 (Age) – 17.1102 (Frequency of Visits) + 0.0375 Length of Relationship) + 3.9007 (Total Spend) + 0.4141 (Agent) + 0.4989 (Call-In) + 2.5531 (Social Media) – 6.0672 (Seminar) – 0.0845 (Recommender) – 0.2365 (Free Promotion) + …..

$H_2$ = tanh (-9.7601 – 4.2983 (Age) – 1.48008 (Frequency of Visits) + 1.0828 (Length of Relationship) – 2.3431 (Total Spend) + 0.7112 (Agent) – 9.4258 (Call-In) + 6.2147 (Social Media) – 0.8863 (Seminar) – 1.3231 (Recommender) + 0.0691 (Free Promotion) + …..

$H_3$ = tanh (8.3328 – 10.9211 (Age) + 2.3842 (Frequency of Visits) + 2.4608 (Length of Relationship) + 0.0174 (Total Spend) – 0.3472 (Agent) + 1.2299 (Call-In) – 1.9009 (Social Media) + 4.450006 (Seminar) + 0.7142 (Recommender) + 1.1385 (Free Promotion) + …..

**For Nutrition and Ozone Segment**

Logit (Y=1) = -7.600 – 1.4468 $H_1$ + 1.0632$H_2$ + 8.6101 $H_3$

$H_1$ = tanh (-4.6036 – 1.4814 (Age) – 0.9705 (Frequency of Visits) + 0.8504 Length of Relationship) - 12.7299 (Total Spend) + 3.1837 (Agent) – 2.7475 (Call-In) – 0.02601 (Social Media) + 4.5539 (Seminar) – 0.9385 (Recommender) + 0.11008 (Free Promotion) + …..

$H_2$ = tanh (3.4054 – 1.6399 (Age) + 5.8967 (Frequency of Visits) – 0.3445 (Length of Relationship) + 3.2766 (Total Spend) – 0.7931 (Agent) + 0.2389 (Call-In) + 4.7910 (Social Media) + 1.8423 (Seminar) – 3.1315 (Recommender) + 13.1207 (Free Promotion) + …..

$H_3$ = tanh (13.3508 – 0.0218 (Age) + 15.5009 (Frequency of Visits) + 0.6528 (Length of Relationship) + 18.1322 (Total Spend) + 1.0366 (Agent) – 3.7837 (Call-In) – 0.1258 (Social Media) – 2.6165 (Seminar) + 2.9442 (Recommender) + 1.4716 (Free Promotion) + …..

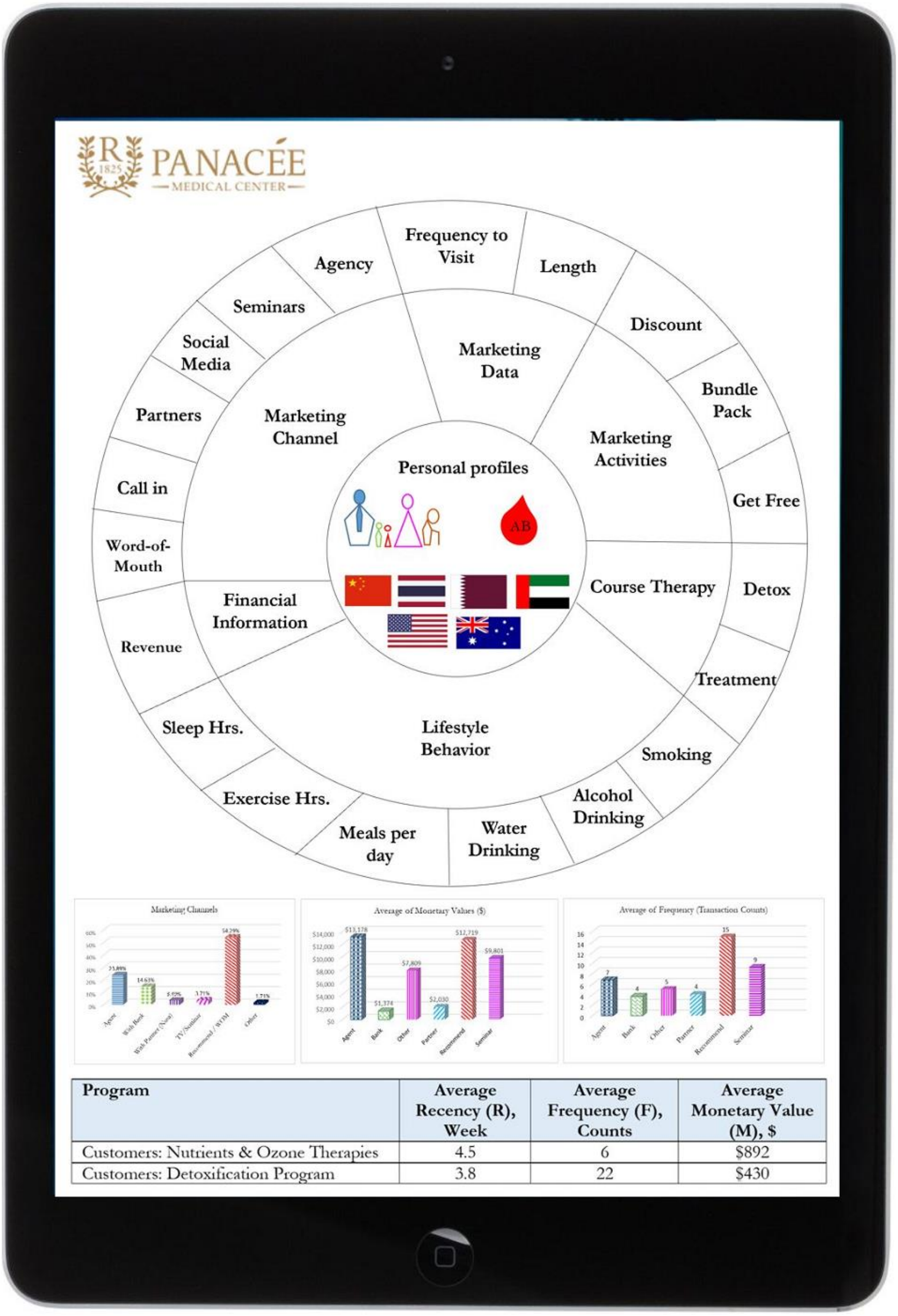



**Figure Appendix A8** The Proposed Executive Dashboard

# Teaching Note

## Applications of Marketing Analytics in Complementary and Alternative Medicine Industry

### I. Synopsis

Dan, the director of a business analytics consulting firm, had been assigned a big project: to help Panacee Medical Center envisage marketing strategies in response to its Beauty and Clinic (B&C) and Natural Health Center (NHC) competitors' recent moves that threatened its sales and current marketing strategies. Dan was working closely with Ben, a newly hired marketing analyst, and Josh, the experienced marketing manager of Panacee, to formulate the medical center's options.

Panacee was one of the leaders in medical treatments and detoxification programs with advanced medical technologies for treatment of various diseases. Last month, however, its main competitor, B&C, surprised Panacee and the rest of the industry by unveiling new, premium treatment therapy services with a touch of relaxation and superior rehabilitation. In addition, NHC, a relative newcomer in the contemporary and alternative medicine (CAM) industry, had invested heavily in advanced laboratory testing facilities that met international standards. Both competitors had taken over first place in their own areas and received positive feedback from their target markets. More damaging, their services were priced 5% to 25% below the established market prices. The combination of low prices and premium services threatened the medical center, and the marketing team had informed Dan that Panacee might lose as much as 30% of its forecast revenue next year.

The services from both B&C and NHC had been timed to prevent a response, especially when the Thailand Health & Wellness Expo, the industry's most important exhibition, was scheduled to take place this coming January. Major customers and tourists would be there; thus, Panacee's new marketing campaigns would determine its sales for the rest of the year. The current strategies Josh had planned for the expo were to offer discounted packages, slashing prices approximately 20% to match or beat both B&C and NHC. Dan and his team had to decide which direction Josh needed to propose to Panacee's top management. Would it be the right decision to engage in the price war with B&C and NHC? Should Panacee stand by its premium pricing strategy and ignore customers who were willing to switch to competitors for the lower prices. Dan needed to make the final decision as to what possible options or strategies were available and the direction Josh should recommend to the top management of Panacee.

**II. Teaching and Learning Objectives:**

- Understand the nature of the complementary and alternative medicine (CAM) Industry
- Understand the concept, pros, and cons of price wars
- Understand what factors/criteria are needed to get more insights about customers.
- Understand the concept of customer segmentation and how to utilize the RFM model and cluster analysis to segment customers based on their similar characteristics.
- Understand how to calculate customer lifetime value (CLV)
- Understand how to utilize the business intelligence framework to justify the decision choices
- Understand how to make decisions in competition-oriented pricing situations

**III. Potential Courses and Target Audiences**

This case is designed to illustrate the applications of marketing analytics that can help analysts develop an understanding of how to analyze customers' behaviors through RFM, cluster analysis, CLV, and marketing channel analysis to make proper decisions in a competitive and price- sensitive environment. This case is primarily intended for MBA students in the course, "BA 7603 — Business Intelligence and Analytics for Firm Decision Making" and other strategic decision-making courses. Additionally, both technology and nontechnology readers can learn how to evaluate decision choices that depend on customer acquisition, customer retention, and customer growth.

Topics Covered in the Case

The following topics are discussed in or raised by the case:

- The Complementary and Alternative Medicine (CAM) Industry
- Customer Segmentation
- Product Life Cycle
- RFM Analysis based on Recency (R), Frequency (F), and Monetary Value (M)
- Cluster analysis based on customers' purchasing behavior.
- Customer Lifetime Value (CLV)
- Business Intelligence
- Price War
- Price Discrimination

## IV. Conceptual Analysis

### Customer Segmentation

Since customer segmentation was introduced in 1956 (Smith, 1956), this concept has been supported by many academic studies and applied successfully by enterprises from various sectors. Customer segmentation can be used to identify and profile distinct groups of buyers who might prefer or require changing products and marketing mixes. The enterprises may decide which segments offer the greatest opportunity, since customers who belong to the same group have certain similarities, while different groups have various characteristics (Kotler & Armstrong, 2018). Specially, customer segmentation helps enterprises understand customer demand and expectations, identify potential customers, and design appropriate marketing campaigns in order to improve business performance. Customers can be classified based on different factors, for instance, general variables—customer demographics (sex, age, income, education level, and lifestyles)—and product- specific variables (frequency of purchase, consumption, spending, and intentions) (Kotler & Armstrong, 2018; Wedel & Kamakura, 2000).

### RFM Analysis

The RFM model scales RFM attributes into 5 equal bins that are assigned the codes 0, 1, 2, 3 and 4 in ascending order; the range within each bin is equal to approximately 20% of all customers. For recency (R), the lower the R-coding, the shorter the time (in weeks, for instance) since the customer's last purchase. In other words, the higher the R-coding, the longer the time (in weeks) since the last purchase. For frequency (F), a low F-coding (count) indicates that a customer rarely places orders with the company. The higher the F-coding, the higher the number of transactions within a defined period. For the monetary (M) value, the lower the M-coding ($), the lower the amount that a customer spent within a defined period. In other words, the higher the M- coding, the higher the amount of money spent. The RFM codes are then used to calculate the RFM score. The five equal bins across these three metrics create 125 (5x5x5) different segments (Miglautsch, 2000). The advantages of the RFM model are that it is a simple and easy method that decision makers can understand and that the model can generally be applied very quickly (Marcus, 1998).

Decision makers can also analyze customer value, assess customer lifetime value, and improve customer segmentation, without any assistance from computer or information systems professionals (Hu & Yeh, 2014). However, RFM analysis considers only three criteria, without considering other attributes such as the relationship between the company and its customers or churn probability. Additionally, RFM analysis cannot distinguish whether the customer's relationship with the company is long-term (a loyalty customer) or short-term. Therefore, some studies have attempted to develop new RFM models either by considering additional variables or by excluding some of the variables according to the nature of the product or service. Many studies extended the RFM by including length (L), where *L* is defined as the number of time periods, such as days, from the first purchase to the last purchase in the database; Time (T), which is defined as the time since the first purchase; or churn probability (C) along with the original RFM metrics (Chang & Tsay, 2004; Peker, Kocyigit, & Eren, 2017; Wei, Lin, Chien, & Wu, 2012).

**Cluster Analysis**

The k-means algorithm is one of the most popular and widely used clustering techniques. K- means clustering applies a standard algorithm that aims to classify objects into multiple subgroups based on the distance of the object to the cluster centroids. The k-means algorithm starts with the random generation of k central points. Then the Euclidian distance between each instance and each centroid is calculated. Each instance is then assigned to the closest centroid. In other words, each instance is assigned to the cluster whose centroid is nearest. It is an iterative approach which computes the value of centroids for each iteration of assigning the instances. The process is repeated until convergence occurs, meaning that the process is stopped when the clusters obtained are the same as those in the previous step. After the clusters are formed, the mean value of each cluster is recalculated based on the current objects in the cluster (Krampe, Strelow, Haas, & Kenning, 2018; Singh, 2018).

**Customer Lifetime Value (CLV)**

CLV was first introduced in the context of marketing as the present value of profit from a customer within a certain period (Berger & Nasr, 1998; Dwyer, 1997) and used to determine the revenue customers are expected to generate over their entire relationship with an enterprise (Dahana, Miwa, & Morisada, 2019; Pfeifer, Haskins, & Conroy, 2005). CLV affects the distribution of promotions, allocation of resources, and other decisions for retaining customers (Kumar et al., 2004). It is calculated differently depending on assumptions which can be classified as scoring models, probability models, econometric models, and mathematic models on the basis of a financial theorem and simulation models. Scoring models employ the concepts of purchasing characteristics such as RFM. Probability models are viewed as an expression of an underlying stochastic process and determined by individual characteristics such as the negative binomial distribution (NBD) model (Glady, Baesens, & Croux, 2009). Mathematical models are based on the NPV financial theorem (Gupta et al., 2006) or a Markov Chain simulation (Ferrentino, Cuomo, & Boniello, 2016).

**Business Intelligence Concept**

Sharda et al. (2017) define Business Intelligence as an umbrella term that combines architectures, tools, databases, analytical tools, applications, and methodologies to aid in decision making. Business Intelligence consists of four components:

1) A Data Warehouse — refers to the source of data in the database management level

2) Business Analytics — refers to a collection of mathematical and statistical tools for analyzing data in the data warehouse

3) Business Performance Management — refers to the process of defining, monitoring, measuring, and comparing key performance indicators

4) A User Interface — refers to the information broadcasting tool or a dashboard, which is a visual presentation of critical data for executives to view and to explore the situation.

**The Components of Business Intelligence (BI)**

Data Management System focuses on the database that contains the data used for analysis. It can be connected to a data warehouse. Collecting and managing data are the first step in developing the business intelligence system. The important tasks in the data management system are not only to integrate data from different sources but also to ensure the data collected is complete, up-to-date, and accurate. Usually, implementing data management systems takes about 60% of the time in implementing BI projects. Poor quality of data usually results in a significant amount of time wasted and high costs of operations.

Model Management System focuses on applying business analytics to solve a particular problem. There are various modeling techniques that can be used to analyze data. Usually a model management system starts from model development using programming languages to model execution.

User Interface System focuses on graphical user interface (GUI) development that allows the user to view, interact, and personalize the dashboard to properly analyze relevant data and make better decisions. In addition to viewing data and information, a good dashboard should be able to link decision making to organizational performance. The outcomes displayed can be in the form or single metrics, graphical trend analysis, geographical maps, or percentage share.

## V. Discussion and Analysis

### 1. Discussion

1) Discuss the pros and cons of a price war.

2) Please list all factors that should be considered in analyzing nutrients and ozone therapies and detoxification campaigns for the upcoming expo.

3) Calculate the customer lifetime value (CLV) for customers in the detoxification segments when the growth rate is estimated a little higher, to 10%, if Panacee combines the detoxification packages with ozone therapy. However, the chance of losing customers to B&C could be up to 30% as well when B&C offers discounted detoxification packages at the Thailand Health & Wellness Expo. The discount rate remains the same at 8%.

4) Please construct the business intelligence architecture for this competition-oriented pricing decision and identify the components and their interrelated functions.

5) Discuss further how AI (deep learning and machine learning) can be used to enhance marketing analytics, especially in such competition-oriented pricing situations.

6) Discuss the possible options for dealing with the B&C and NHC strategies and make the final decision as to which direction Dan should recommend to the top management at Panacee.

### 2. Analysis

1) Discuss the pros and cons of a price war.

**Table Appendix A1** Pros and Cons of Price War

| Pros | Cons |
|---|---|
| 1. Gaining a greater share of the market | 1. Cutting profit margins |
| 2. Providing a better deal for customers Driving competitors out of business | 2. Leading to firm losses and increasing the risk of leaving the market |
| 3. Generating improved cash-flow | 3. Leading to a worse situation when competitors promptly cut prices again |
| 4. Getting rid of perishable stock | |
| 5. Reducing excessive inventories | 4. Hurting brand image and credibility |

2) Please list all factors that should be considered in analyzing nutrients and ozone therapies and detoxification campaigns for the upcoming expo.

- Type of Products or Services
- Competitor Analysis
- Market Share
- Product Life Cycle
- Cost of Services
- RFM Analysis
- Customer Lifetime Value
- Cluster Analysis
- Marketing Channels Analysis
- Target Markets
- Price vs. Perceived Value
- Price Discrimination

3) Calculate customer lifetime value (CLV) for customers in the detoxification segments, when the growth rate is estimated a little higher, to 10%, if Panacee combines the detoxification packages with ozone therapy. However, the chance of losing customers to B&C could be up to 30% as well when B&C offers discounted detoxification packages at the Thailand Health & Wellness Expo. The discount rate remains the same at 8%.

$$CLV_{avg.} = \$430 + \frac{\$430 * 1.10 * 0.7}{1.08} + \frac{\$430^2 * 1.10^2 * 0.7^2}{1.08^2} + \frac{\$430^3 * 1.10^3 * 0.7^3}{1.08^3} + \ldots + \propto$$

$$CLV_{avg.} = \frac{\$430}{0.08 + 0.3 - 0.10} \approx \$1{,}536$$

4) The BI architecture can be developed as follows: The data layer should include customers' profiles for both detoxification and nutrition and ozone therapies (Transaction-based data — recency, frequency, monetary value, and length of relationship), detailed packages for both treatment programs, revenues, cost of services, marketing channels, and price packages for Panacee and its competitors. The

BPM layer should measure the key performance indicators for each therapy program. These KPIs should include CLV, market share, profit, revenue, intention to respond to future campaigns, customer retention, and customer acquisition. The business analytics layer refers to the mathematical models such as CLV calculation, RFM analysis, cluster analysis, logistic regression model, and neural network model. The user interface summarizes in a single window the information needed to make a decision (see Figure 1).

5) Discuss further how AI (deep learning and machine learning) can be used to enhance marketing analytics, especially in such competition-oriented pricing situations.

Artificial intelligence (AI), deep learning, and machine learning represent powerful learning algorithms enabling computers or machines to learn from data, often called “experience,” where the term “learning” focuses on the acquisition of knowledge from the existing data to create a hypothesis that can predict the desired target, in this dissertation to predict whether the existing customers are likely to respond to future campaigns. Additionally, the term “learning algorithm” is an analogy to a simplified form of human learning that happens quickly. Compared to conventional regression analysis, these algorithms encompass a wide variety of techniques to identify intrinsic patterns in data. Deep learning, on the other hand, is just another term describing a certain type of neural network model. By processing the data through multiple hidden layers with multiple hidden units of nonlinear transformations of the input data in order to predict the desired target, artificial neural networks and the more complex deep learning algorithms are capable of solving very complex problem. As a result, the performance of the developed models, which in this dissertation is measured based on criteria such as false negatives, prediction accuracy, and misclassification rate, can be measured more accurately than logistic regression or decision tree models, which are very popular data mining techniques.

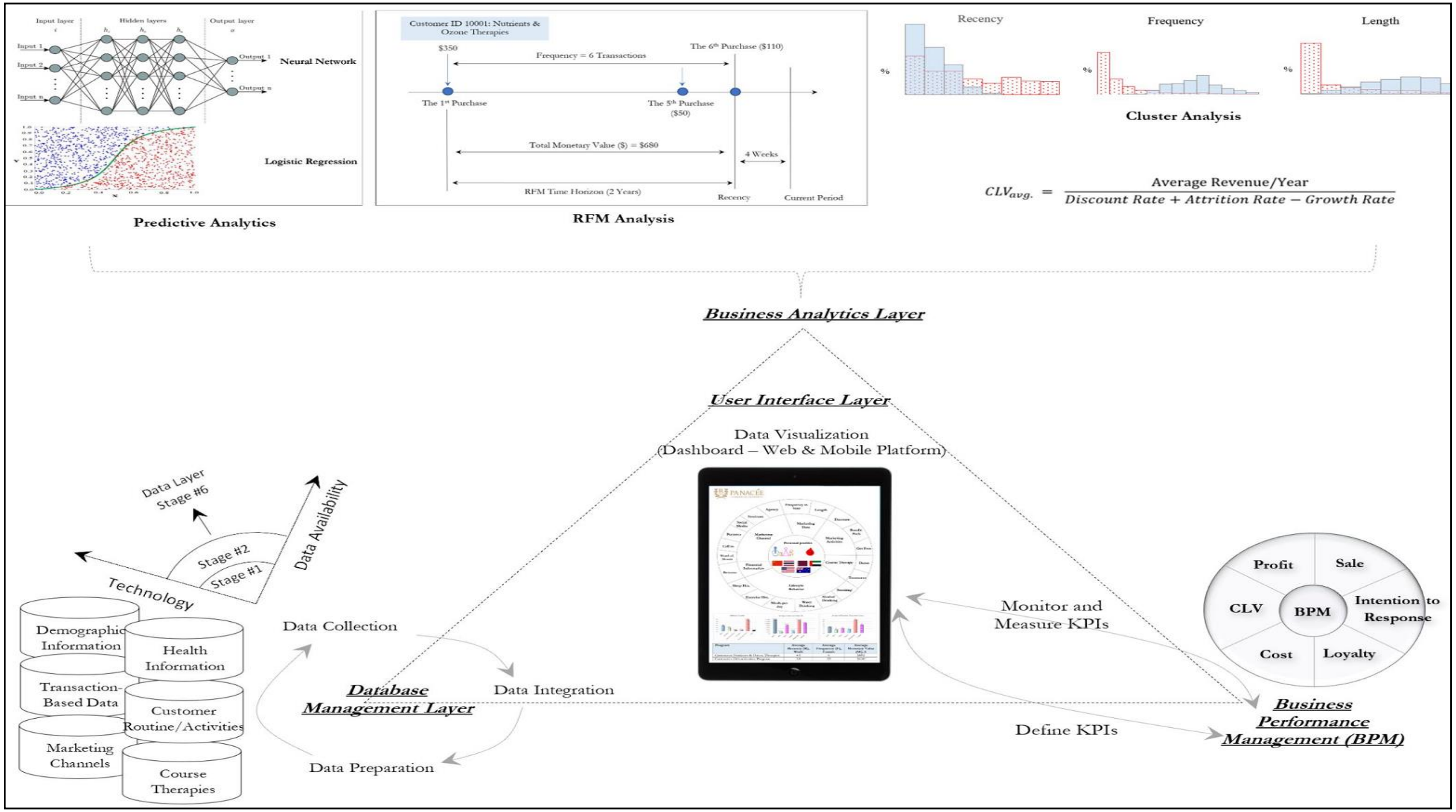



**Figure Appendix A9** The Business Intelligence Architecture

6) Discuss the possible options for dealing with the B&C and NHC strategies and make the final decision as to which direction Dan should recommend to the top management at Panacee.

**Table Appendix A2** Marketing Information by Therapy Programs

| | **Detoxification Programs** | **Nutrients & Ozone Therapies** |
|---|---|---|
| Market Share | Panacee 30%<br>B&C 10%<br>NHC 3% | B&C 35%<br>NHC 15%<br>Panacee 5% |
| Cost of Services (both Direct and Indirect Costs) | 65% | 55% |
| Average Recency (R) | 3.8 Weeks | 4.5 Weeks |
| Average Frequency (F) | 22 Transactions | 6 Transactions |
| Average Monetary Value (M) | $430 | $892 |
| Growth Rate | 5% | 25% |
| Attrition Rate | 10% | 40% |
| Average CLV | $3,308 | $3,878 |
| Cluster Analysis | Cluster #1: Loyalty Customers | Cluster #2: Big Spenders |
| Overlapping Customers | Not a lot but High Value | |
| Marketing Channels (Expo) | Mostly Loyalty Customers | Mostly Tourists |
| Logistic Regression and Neural Network Models | | |
| - Most Effective Channels | Agents, Call Centers, Seminars | Social Media, Word-of-Mouth |
| - Free-Promotional Campaigns | No | Yes |
| - Probability to Respond to the Future Campaign (Scoring on the relatively new customers) | 68% | 43% |

Before making any decision, it is important to tie decisions to business goals and direction. This is the first question Dan needs to ask top management about the current strategies and expectations.

**Option #1: Decision to Fully Engage in Competitive Price Strategies for a Short Period of Time**

**Option #2: Decision to Stay at the Premium Price on both Nutrients & Ozone Therapies and Detoxification Program**

**Option #3: Decision to Stay at the Premium Price on Detoxification Program,**

**Offer Discounted Packages on Nutrients & Ozone Therapies**

Options #1 and #2 are extreme cases. If top management insists that the STP (Segment, Target, Positioning) of Panacee is targeting premium customers with the premium price, Option #2 should be employed, that is, standing by the premium price and focusing on the customers who care more about value than price. Another important point is that if Panacee decides to engage in the price war, what will happen? or how should Panacee respond if both B&C and NHC promptly cut their prices again?

If top management decides that lowering the price just for this expo will not hurt brand image, creditability, and margin, Option #1 is possible to gain a little bit of market share and, sort of, reward its customers with a great deal.

Option #3 is between the first two options. Panacee is a relatively big medical center with multiple products, so it can drastically reduce prices in one program, while still reaping profits in others. Detoxification programs have been highly rated, flagship products for years, while nutrients and ozone therapies are still relatively new to the market. Partially discounting new services will not hurt its reputation and might be worthwhile to penetrate the nutrients and ozone therapies market, where its market share is quite far behind its competitors.

**Option #4: Decision to Bundle Nutrients & Ozone Therapies and Detoxification Programs for Discounts (Price Discrimination Strategy)**

**Option #5: Decision to Provide a Discount for a Certain Group of Customers, e.g., Foreign Customers or Students.**

The assumption in Options #4 and #5 is that Panacee is trying to survive a competition- oriented pricing situation, rather than trying to win it. When engaging in the price war is not likely to happen, price discrimination strategies are possible. Panacee can offer a special 10% promotional discount, as in the examples Josh provides: when customers purchase both the detoxification program and the nutrients and ozone therapies together (Option #4), offer campaigns like “Buy 10 treatment courses, Get a 10% discount or 2 free additional treatments,” or provide special discounts for certain groups (Option #5), such as foreign customers, etc.

**Option #6: Decision not to Participate in the Expo.**

Another extreme option is to recommend to top management that Panacee skip the expo this coming January. One might argue that participating in the trade and exhibition is a must as a key marketing strategy to promote sales of a variety of services, to share updated information about its services, and to establish relationships or negotiate deals with its loyalty and potential customers. However, even what Panacee invested in the Thailand Healthcare+ Expo in June this year has not yet been recovered. Participating in the Thailand Health & Wellness Expo this coming January with even more pressure (price, new facilities, and international standards) from its competitors without any new services might not be worthwhile. This option is worth considering and cannot be easily ignored.

## VI. Teaching Plan

The case study should be used as a practicum exercise in a 2-to-3-hour class discussion. The case study is divided into three parts.

- Case A is intended to provide an overview of Panacee Medical Center and its competitors. Students should be familiar with the CAM-related healthcare business. Students should start thinking about the pros and cons of price wars and what factors need to be analyzed (the analytical framework) as a marketing analyst in that competitor-oriented price situation.

- Case B is all about insights into customers. Students should start the analysis from the overview of market share (external analysis) and move toward the internal analysis such as cost of services. Customer segmentation can provide some insights into the customers based on both CLV and transaction-based data (recency, frequency, and monetary value).
- Case C focuses more on marketing channel analysis and the importance of perceived value and price factors in purchasing decision. Some of the marketing strategies are hinted at. Along with the key findings from customer segmentation and customer lifetime value, students should be able to come up with different options to cope with the price war situation.

**Expected Flow of Discussion & Key Issues to Raise at Specific Points**

**Case A** — can be distributed as a homework assignment or at the beginning of the class.

**For Discussion Question #1 (Estimated time: 30 minutes)**

Students are required to discuss situations where a price war can happen and why competitors decide to drop their prices. Instructors can ask students to give several examples of recent price wars. For instance,

- The case of Amazon's Kindle products: The first kindle was priced at $399; the current lower- end-Kindle is priced at $139.
- The case of the airline industry (the low-cost vs. premium airlines), which is a classic example of an environment for a price war.
- The leading supermarkets often engage in extensive price-cutting for products during holiday events.

Then students list the pros and cons of price wars and how these factors can be applicable in the context of the complementary and alternative medicine (CAM) industry.

**For Discussion Question #2 (Estimated time: 20 minutes)**

Students should be able to outline the plan for analysis, defining what data or factors need to be considered before engaging the competition-oriented prices from B&C and NHC. Of courses, it is fine if students cannot list all relevant factors that should be considered in analyzing the nutrients and ozone therapies and detoxification campaigns for the upcoming expo. The goal of Question #2 is just to encourage students to think about the analytical framework. Instructors can come back to this question again after going through the case.

**Case B** — be distributed after Questions #1 and #2 are discussed can

**For Discussion Question #3 (Estimated time: 10 minutes)**

Each student is required to calculate the customer lifetime value (CLV) for customers in detoxification programs when the estimated parameters (growth rate, attrition rate, and even discount rate) changes. Instructors should also conclude the discussion by pointing out that the calculation of CLV is an example of a technique frequently used in marketing analytics. At this point, students should come up with decision choices to help Dan and Ben prepare an executive report. After receiving more valuable information about customers with regard to market share, cost of services, RFM analysis, customer lifetime value, and cluster analysis for customers in both the nutrients and ozone therapies and the detoxification programs, students should be able to evaluate what options are available in order to respond to the reduced prices B&C and NHC will offer at the Thailand Health & Wellness Expo and in which direction it would be reasonable for Panacee to proceed.

**Case C** — can now be distributed after Question #3 and decision choices are discussed

**For Discussion Questions #4, #5, and #6 (Estimated time: 60-90 minutes)**

The instructors should first focus on the database subsystem and explain the importance of capturing the relevant data needed to make a decision, emphasizing on how data is gathered, stored, and accessed in the database. The concept of business performance management, business analytics and user interface subsystem are then explained. The instructors might ask students to construct the architecture of business intelligence for this pricing decision. Lastly, for the business analytics, the instructors have to ensure that students understand the concept of the logistic regression and neural network models to predict how customers are likely to respond to the future campaign.

After getting more information on marketing channel analysis, target market, price and perceived value, and a price discrimination strategy, each student should come up with their final decision choices. Students should specify what factors justify their decision. Instructors should emphasize that there are no right or wrong decisions, as the objective of the case study is to demonstrate how to utilize data to make a good decision. Again, students should know that they need to tie their decision to the direction and goals of the business.

## VII. Research Methodology

This case study was part of research conducted at Panacee Medical Center. The details on how to calculate RFM, cluster analysis, and customer lifetime values can be found in the following two studies.

### Integrated Customer Lifetime Value (CLV) and Customer Migration Model to Improve Customer Segmentation (Author, 2020)

The RFM model and cluster analysis are widely used to gain a deeper understanding of customers' characteristics and needs because of its simplicity and applicability in analyzing customer purchasing behavior. However, the lack of incorporating the future value of customers and whether current customers exhibit a pattern of likely attrition or switching to a competitor into the original segmentation models is a big concern in segmenting customers for further strategic and personalized campaigns. How can organizations integrate their customers' lifetime value and customer migration, which refers to the probability that their customers will return in the future, as parts of the RFM and cluster analysis to improve marketing decisions? The modified segmentation models are then validated in the context of complementary and alternative medicine in the healthcare industry to demonstrate the practical validity of our proposed methods.

**Integrated Customer Lifetime Value Models to Support Marketing Decisions in Healthcare (Author, 2020)**

Many organizations continually look for ways to understand their customers' behaviors and maintain outstanding relationships with them. One of the key indicators for handling such challenges in customer relationship management is customer lifetime value (CLV), which measures the success or health of an organization by estimating the net value its customers contribute to the business over the lifetime of the relationship. How can the organizations assess their customers' lifetime value and offer relevant strategies to retain the prospects and profitable customers? This study offers an integrated view of different methods to calculate customer lifetime values by considering scenarios ranging from both finite and infinite customer lifetimes to customer migration and Monte Carlo simulation models. These models are validated in the context of complementary and alternative medicine in the healthcare industry. The results show that understanding CLV can help the organization develop strategies to retain valuable customers while maintaining profit margins.

## VIII. References and Suggested Advanced Reading Assignments and Class Handouts

To make sure students have the required knowledge concerning the marketing analytics concepts prior to the class discussion, the following list of suggested readings can be assigned with the assignment of the case.

1) Jackson, J. (2002), "Data mining: A conceptual overview," *Communications of the Association for Information Systems*, Vol. 8 No. 1, pp. 267-296.

2) Raju, J. (2014). *Competitive Marketing Strategy, NIDA Executive Leadership Program*. Presentation at The Wharton School of the University of Pennsylvania, October 13-17, 2014

3) Sharda, R., Delen, D., Turban, E. (2017). *Business Intelligence, Analytics, and Data Science: A Managerial Perspective on Analytics,* 4th Edition, city, NJ: Pearson.

4) Sharda, R., Delen, D., Turban, E. (2019). *Analytics, Data Science, and Artificial Intelligence: Systems for Decision Support,* 11th Edition, city, NJ: Pearson.

# BIOGRAPHY

| | |
|---|---|
| **NAME** | Miss Kessara Kanchanapoom |
| **ACADEMIC BACKGROUND** | Bechelor of Accounting, Dhurakijpundit University<br><br>Bechelaor of Chinese Language (Economics and Trade), Beijing Language and Culture University (Bangkok)<br><br>Master of Business Administration, Bangkok University<br>Master of Business Administration (Marketing), Mahanakorn University of Technology |
| **PRESENT POSITION** | Rattanakosin International College of Creative Entrepreneurship, Rajamangala University of Technology Rattanakosin |