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PRODUCT PRICING WITH MARKETING DATA UNDER RISK USING BUSINESS INTELLIGENCE

PREÇOS DE PRODUTOS COM DADOS DE MARKETING SOB RISCO USANDO INTELIGENCIA PARA OS NEGOCIOS

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Abstract: Since product pricing is a significant decision for producers and is known as a challenging problem in today's marketing operations, the aim of this study is to design an integrated decision support system for pricing. The emerging business environment is highly dynamic in which only companies being higher in terms of competitiveness can succeed in achieving a sustainable market. Nowadays, most companies often use complicated information systems such as business intelligence systems for effective decision making and analytics. Here, by using pricing methods the prices of products are determined on the basis of marketing data under the terms of risk so that to maximize revenue along with fulfilling customers' demands. A case study is reported to show the effectiveness of the approach. There, we analyzed different effects of our proposed pricing models and studied the influences on the purchase behavior of the customers.

Keywords: Business intelligence, Pricing, Risk, Marketing data.

Resumo: Como o preço do produto é uma decisão significativa para os produtores e é conhecido como um problema desafiador nas operações de marketing de hoje, o objetivo deste estudo é projetar um sistema integrado de suporte à decisão para determinação de preços. O ambiente de negócios emergente é altamente dinâmico, no qual apenas as empresas que são mais altas em termos de competitividade podem obter sucesso em alcançar um mercado sustentável. Hoje em dia, a maioria das empresas costuma usar sistemas de informações complicadas, como sistemas de business intelligence, para tomadas de decisões e análises eficazes. Aqui, usando métodos de precificação, os preços dos produtos são determinados com base em dados de marketing sob os termos de risco, para maximizar a receita e atender às demandas dos clientes. Um estudo de caso é relatado para mostrar a eficácia da abordagem. Lá, analisamos diferentes efeitos de nossos modelos de precificação propostos e estudamos as influências no comportamento de compra dos clientes.

Palavras-chave: inteligência de negócios, preços, risco, dados de marketing.

1 INTRODUÇÃO

Environment is complex, opportunities are changing constantly and new threats come together. Companies and their strategic system should always be supervised by environment which requires large amounts of information, including information systems, market researches and consumer markets evaluation [1]. Companies need every aspects of information to provide higher value and customer satisfaction. They should have so much information from competing companies, middlemen and other factors that are active in the market. This large amount of data must be processed to become valuable knowledge for effective decision making; so often complex information systems such as Business Intelligence systems are used [2].

Business Intelligence Systems provide capabilities such as business information analysis in order to support and improve decision-making management in a wide range of business activities and also provide for managers easy to use, timely and appropriate information at different organizational levels and enable them to make better decisions [3]. Business Intelligence systems can be defined as systems that provide a set of structured data stored and updating from different sources [4]. These systems allow managers to dynamically work with data that are changing, analyze them and understood what ultimately led to the acceleration of earning the relevant information and their effective application in monitoring and decision-making process in the company [5]. Using business intelligence can simplify explore and analyze information and allow decision makers to easily access their information anywhere and anytime and understand and analyze them better and simplify decision-making and provides the advantages in all areas and activities, including helping in the analysis of market share, changes in customer behavior, pattern costs, preferences of customers, respond quickly to customer needs, forecast market situation, appropriate reaction with respect to changes in the market, retain customers and discover their specific requirements, reducing costs and increasing customer satisfaction [6].

It should be noted that in today's dynamic and changing environment, customers willing to use the products and services with high quality and low prices on the one hand and to improve customer relationship on the other hand [7]. Business intelligence and customer relationship management systems play a key role in achieving and maintaining competitive advantage. Business Intelligence helps businesses to understand their customers better and help them to adapt themselves with demands of customers [8].

Nowadays, business organizations need to analyze the market so that in dealing with market changing can remain constant and finally be able to manage market [9]. For this purpose, organizations should update their business processes using modern technologies that are called business intelligence. In fact, business intelligence enables managers to adapt their decisions with their knowledge of market intelligence, tactics and business investment as well as a systematic process to ensure accurate and updated information related to competitors [1,10].

Product pricing decisions are main core of any business marketing and have a direct impact on corporate business strategy. Price is the benefit that consumer pay for benefits of having or using the product [10]. Simply pricing means set the prices for goods or services. Pricing is an activity that should be repeated and the process is continuing. The continuing resulting from environmental changes and market conditions instability that creates price adjustment. Pricing is done to maximize profit, increasing market share, and quality leadership or increase market prices [11]. Reasonable price is the price that satisfies the needs of the seller and the buyer at the same time. If the price set is optimized, more satisfied customers and higher profits will be expected for seller. Pricing is nothing more than set prices. This includes a strategy for increasing sales volume to achieve a profit and also creating and sending a message communication is to demonstrate the value that your product create for customer and the company may be faced with losses by a wrong decision about price [11].

The aim of this research is to design an integrated decision support system using pricing methods to determine the price of products based on marketing data under the terms of risk. The marketing data may not be necessarily accurate and uncertainty is considered. These data are refined integrated and stored using extract, transform and load (ETL) tools to analyze business intelligence. Then, these data are used by pricing models under decision support system for analysis and decision-making so that effective decisions, timely and appropriate measures are taken where the output of the model is prices for business firms, in such a way maximizing revenue from sales and customers' demands fulfillment.

The paper is organized as follows. The methods and materials used in this study are introduced in the next section. The proposed model is then presented in Section 3. Implementation of the proposed model is conducted as a case study in Section 4. Finally, we conclude and express limitations and directions for future research in Section 5.

2 MATERIALS AND METHODS

There are two firms indexed by $i = A, B$. The firms produce homogeneous services (or goods). Consumers gain utility $\bar{u}$ from consumption, which means that $\bar{u}$ is the maximum amount that they are willing to pay for the service [12]. Two "demographic" parameters are defined to introduce growth (decline) in the population of consumers as follows:

(a) Consumers enter the market at a rate $\beta \geq 0$ (entry rate).

(b) Existing consumers exit the market at a rate $\delta \geq 0$ (exit rate).

New consumers purchase when they enter the market and thereafter become locked in with the firm they initially chose to purchase from. Existing customers purchase at a unit rate. More specifically, in a period of length *dt*, conditional on not exiting the market, an existing consumer purchases with probability 1*dt*. In aggregate, since there are *N(t)* existing (locked-in) consumers, the expected number of purchases by locked-in customers is *N(t)dt*. This means that, in a period of length *dt*, new consumers buy $\beta N(t)dt$ units (since there are $\beta N(t)dt$ entering consumers during *dt*) and existing consumers buy *N(t)dt* units, whereas consumers who exit the market do not buy during the time interval *dt*. Thus, the proportion of products purchased by new consumers is [12]:

$$\frac{\beta N(t)dt}{\beta N(t)dt + \mathrm{N(t)dt}} = \frac{\beta}{\beta+1} \epsilon\ [0, 1). \qquad (1)$$

To ensure that the market is fully covered, we assume that the utility rate $\bar{u}$ is sufficiently high such that all consumers subscribe to the offered service (buy the offered goods). A sufficient condition for the market to be covered under the two pricing regimes to be analyzed (history based pricing and uniform pricing) [12]. Note that, we consider the rate of willingness to pay is bounded from below. Formally, $\bar{u} > 2 + \frac{1}{\beta}$.

2.1 DYNAMIC PROFIT MAXIMIZATION

Firm *i* has a market share of $\sigma_i^L(t)$ at time *t* among locked-in consumers and $\sigma_i^N(t)$ among new consumers with the shares for firm *j* being $\sigma_j^L(t) = 1 - \sigma_i^L(t)$ and $\sigma_j^N(t) = 1 - \sigma_i^N(t)$ respectively. With differentiated pricing firm *i* sets the price $p_i^N(\sigma_i^L)$ for new consumers and $p_i^L(\sigma_i^L)$ for locked-in consumers. These prices are contingent on the state variable σ_i^L. Note that, σ_i^Ni is not a state variable since it can be changed instantaneously through current period prices. Under uniform pricing we consider, $p_i^N(\sigma_i^L) = p_i^L(\sigma_i^L) = p_i^U(\sigma_i^L)$ (Shy, 2016). Firm *i*'s instantaneous profit and time discount rate are denoted by $\pi_i(t)$ and ρ^f. Assuming zero production cost, at each period t_0, firm *i* chooses a continuous time price strategy $(p_i^N(\sigma_i^L) = p_i^L(\sigma_i^L))$ to maximize the value function given by:

$$V_i(t_0) = \int_{t_0}^{\infty} e^{-\rho^{f(t-t0)}} \pi_i(t)\mathrm{dt}, \mathrm{i} = \mathrm{A}, \mathrm{B}, \qquad (2)$$

where,

$$\pi_i(t) = N(t_0)e^{n(t-t0)}[p_i^N(t)\beta\sigma_i^N(t) + p_i^L(t)\sigma_i^L(t). \qquad (3)$$

Also, note that firms discount the future more heavily than the net growth rate of the consumer population.

At the time of adoption, the new consumers who are entering the market choose a brand to maximize a discounted stream of utilities with a discount rate ρ^c. Recall that consumers have heterogeneous initial adoption costs. Each new consumer entering at t_0 chooses a brand *i* according to

$$argmaxU_i = \bar{u} - \tau_i - p_i^N(t_0) + \int_{t_0}^{\infty} e^{-(p^c+\delta)(t-t_0)} [\bar{u} - p_i^L(t)dt. \qquad i \in \{A,B\} \quad (4)$$

The first three terms in (4) constitute the initial utility net of adoption cost and the introductory price. Combined with the last term, (4) implies that consumers choose the brand that yields the highest value net of brand adoption cost, current price, and net of all discounted future prices during the consumers' lifetime when the consumers are locked in with the chosen brand. Consumers discount the future by $e^{-(p^c+\delta)(t-t_0)}$. As seen in (4), the discount rate $\rho^c$and the exit rate δ have similar effects on the consumers' brand selection. The parameter δ determines the expected duration of customer relationships and thereby the industry growth rate *n*. This parameter influences firms' return from an acquired customer relationship and thereby the intensity of competition for new customers.

2.2 HISTORY-BASED PRICING

With history-based pricing (HBP), firms differentiate the price targeted for entering consumers from the price offered to locked-in consumers. More precisely, this pricing regime focuses on competition when firms charge two prices: $p^L(\sigma_i^L)$ to their existing (locked-in) customers, and

$p^N(\sigma_i^L)$ to new customers. With history-based pricing, the unique model is given by (Shy, 2016):

$$p^{L_*} = \bar{u} \quad and \quad p^{N_*} = 1 - \frac{\bar{u}}{\rho^f+\delta}, for\ all\ \sigma_i^L \in [0,1], \qquad (5)$$

yielding an average price of,

$$p^{-HBP} = p^{N_*}(\frac{\beta}{1+\beta}) + p^{L_*}(\frac{1}{1+\beta}) = 1 - \frac{\bar{u}}{\rho^f+\delta}(\frac{\beta}{1+\beta}) + \bar{u}(\frac{1}{1+\beta}), \qquad (6)$$

at each point in time.

From (6) we can infer that the price targeted to existing customers, $p^{L_*} = \bar{u}$, as well as that targeted to entering consumers without history, $p^{N_*} = 1 - \frac{\bar{u}}{\rho^f + \delta}$ are each independent of the rate of consumer entry β. In fact, with history-based pricing the rate of consumer entry only affects the proportions of consumers targeted by p^{L_*} and p^{N_*} respectively. Thus, the rate of consumer entry only affects the average price associated with history-based pricing. This average price is nevertheless important as it determines the profit rate of firms, firm value, and the rate of consumer surplus. An increased entry rate of consumers (higher β) implies a reduced average price, meaning that an increased entry rate makes the investment effect stronger. On the other hand, a reduced β implies a higher average price as it makes the harvesting affect stronger [12].

2.3 MULTI-FACTOR RISK PRICING MODEL

Managing risk lies at the heart of the financial services industry [13]. The financial risk pricing approach has been developed within the framework of a linear multi-factor regression model. This framework offers a systematic way of describing how expected returns of assets (e.g., stocks, projects) vary with the movement of their associated risk factors. A risk variable *j* is an uncertain observable characteristic of an asset or its contextual environment. A risk factor *j* is defined as the deviation of the ex-post value of risk variable *j* from its ex-ante expected value [14]. Assuming *j* risk factors, the finance literature commonly starts with the next return-generating process (RGP) specification as a way to explain the prices of traded assets:

$$\widetilde{r_i} - \overline{r_i} = \beta_{i,1}\widetilde{f_{i,1}} + \cdots + \beta_{i,J}\widetilde{f_{i,J}} + \varepsilon_i \, (i = 1, \dots, n \, , j = 1, \dots, J) \qquad (7)$$

where $\tilde{f}_{i.j}$ is a stochastic mean-zero risk factor $\beta_{i,j}$ is a factor sensitivity indicator measuring the degree of exposure of asset *i* to risk factor $\tilde{r}_i$ is the stochastic risk-adjusted return on asset *i*; $\overline{r_i}$ is the return expected if all factor sensitivities are zero; and ε_i is residual risk having an expected value of zero [14]. A central assumption of the finance literature on pricing risk from the perspective of market investors is that only systematic (macro-economic) risk factors matter and command a premium return. As a result, this literature relies on a version of the RGB specification in (7) which requires that all assets should experience identical factor realization values, that is,

$$f_{i,j} = f_{i,k} \; \forall i, k \; (i, k = 1, \dots n) \quad . \qquad (8)$$

3 PROPOSED MODEL

Our proposal model includes three stages that are explained below and illustrated in Figure 1:

Stage 1 - data collection: first the required data from various sources are collected from customers in the marketing environment and the data may not necessarily be accurate (uncertainty).

Stage 2 - extracting data from databases into a single repository: At this stage the data using ETL tools are refined, integrated and stored to analyze business intelligence.

Stage 3 - then the data are used by pricing models and multifactor risk pricing models under decision support system for analysis and decision-making and provide optimal price.

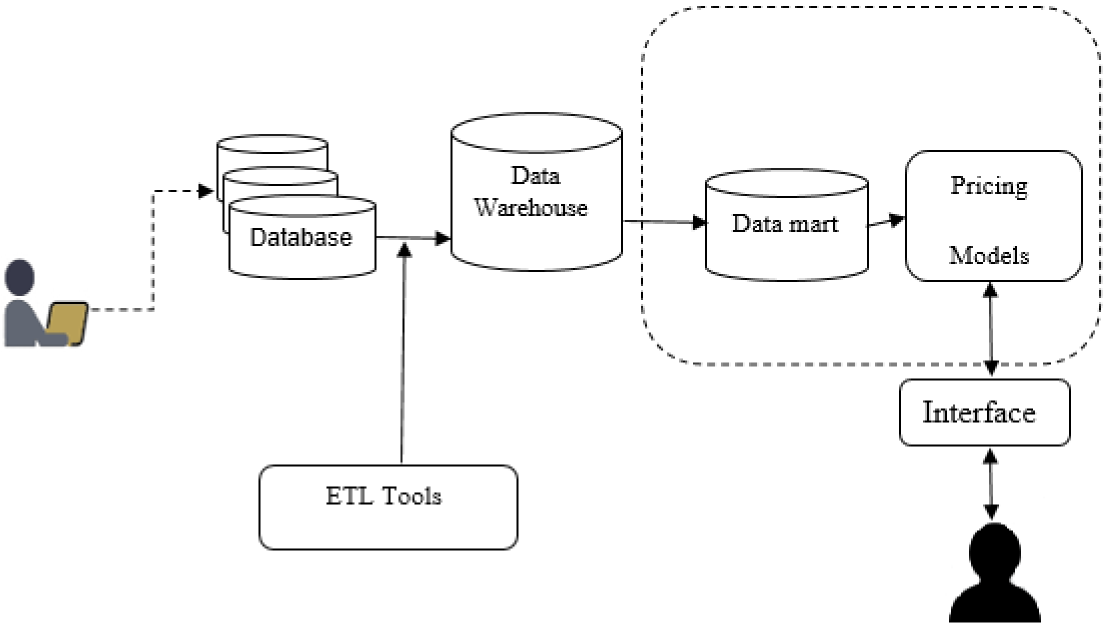

Figure 1. Proposed model

4 RESULTS

In this section, we implement this system for a food distribution company. The main activity of food distribution companies are import, export and distribute a comprehensive variety of products such as tea, oil, rice, sugar, beans, tuna, paper towels, soap and more.

Stage 1 - Data collection

Data are collected from customers of a food distribution company during a year. This company was studied during a year in which its products are sold to 76 customers. The company sells products such as tea, oil, rice, tuna, paper towels, tomato paste, ketchup, mayonnaise, macaroni, and dishwashing liquids. Some information is shown in Table 1.

Table 1. Products and companies

Product name	Company name	Discount rate
Oil	Company 1	**%5**
Tea	Company 2	**%3**
dishwashing liquids	Company 3	**%4**
ketchup	Company 4	**%2**
tuna	Company 5	**%4**
Rice	Company 6	**%6**
macaroni	Company 7	**%4**
paper towels	Company 8	**%3**
mayonnaise	Company 9	**%2**
tomato paste	Company 10	**%3**

Table 2 shows entry rates for new and locked in customers as well as exit rate for products of a food distribution company.

Table 2. Entry and exit rates of customers

Product Name	Entry rate of lock in customers	Entry rate of new customers	Exist rate of customers
Oil	47	12	**5**
Tea	24	8	**3**
dishwashing liquids	53	15	**3**
Ketchup	59	14	**4**
Tuna	49	9	**3**
Rice	48	6	**4**
Macaroni	32	5	**5**
paper towels	27	4	**3**
Mayonnaise	34	5	**6**
tomato paste	30	6	**4**

Stage 2 - Extracting data from databases into a single repository

Now, the data is collected may include repetitive and redundant data or excessive data that need to be refined, integrated and saved using ETL tools to be analyzed in business intelligence database. According to Figure 2, first specific tables from the data source are chosen to load required data for measuring. Then, the data are transferred to the operational level and ETL process that involves three stages of extraction, transformation and loading being done for extraction, cleaning, customization and loading data. The extracted and refined data are transferred into the data warehouse and data mart for analysis by end users.

Figure 2. ETL process

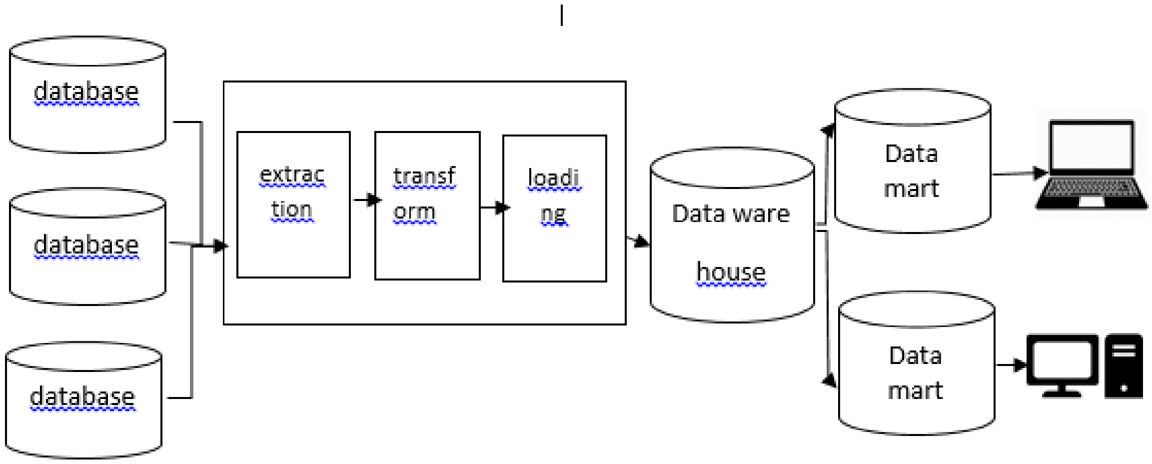

Table 3 is the output of the ETL process, which includes required data to calculate prices using pricing model based on history.

Table 3. The output of the ETL process

Product Name	Discount rate	Exist rate of customers	Entry rate of new customers	Entry rate of lock in customers
Oil	0.05	5	12	**47**
Tea	0.03	3	8	**24**
dishwashing liquids	0.04	3	15	**53**
Ketchup	0.06	4	14	**59**
Tuna	0.02	3	9	**49**
Rice	0.03	4	6	**48**
Macaroni	0.04	5	5	**32**
paper towels	0.02	3	4	**27**
Mayonnaise	0.03	6	5	**34**
tomato paste	0.04	4	6	**30**

Stage 3- Applying history-based pricing model

At this stage data are used by history-based pricing model for analysis and decision-making leading to determining products' prices. The results of the calculations are presented in Table 4. The unit measure is 1000$. For example, the average price for oil is obtained 0.61 that indicates the average price of 610$.

Table 4. Prices considered for new and lock in customers and the average price of products

Product Name	p^{-HBP}	p^{N_*}	p^{L_*}	Utility rate New customers	Utility rate Lock in customers	ρ^f	δ	Entry rate of New customers	Entry rate of lock in customers
Oil	0.61	0.59	2.05	2.11	2.05	0.05	5	12	**47**
Tea	0.37	0.3	2.07	2.15	2.07	0.03	3	8	**24**
dishwashing liquids	0.33	0.32	2.04	2.09	2.04	0.04	3	15	**53**
ketchup	0.50	0.49	2.04	2.1	2.04	0.06	4	14	**59**
Tuna	0.33	0.3	2.05	2.14	2.05	0.02	3	9	**49**
Rice	0.52	0.5	2.05	2.19	2.05	0.03	4	6	**48**
macaroni	0.32	0.27	2.06	2.23	2.06	0.04	5	5	**32**
paper towels	0.36	0.32	2.06	2.28	2.06	0.02	3	4	**27**
mayonnaise	0.66	0.64	2.05	2.23	2.05	0.03	6	5	**34**
tomato paste	0.53	0.49	2.06	2.1	2.06	0.04	4	6	**30**

Now by using equation (7) that is a multi-factor pricing risk model, we specify the importance of the risk factors on the profit of products. To simplify, equation (7) is a regression model that is used for calculation of coefficient β . First, we should collect data to run regression equation and derive coefficients that is being done by statistical software. The percentage of varying risk factors such as inflation, rate of arrival of customers, customers' exit rates, depreciation, utility rate of lock in customers and profit rate added on liquid oils are shown in Table 5.

Table 5. Risk factor profit forecast

month	1	2	3	4	5	6	7	8	9	10	11	12
Inflation risk factor (%)	2.1	1.2	1.5	1.4	1.3	1.8	1.6	2.3	1.4	1.8	1.2	2.4
(%)Risk factors of customer Exit rate	2.7	1.38	2.5	2.83	2.7	2.6	1.35	2.3	1.4	2.4	1.5	1.8
Risk factors of customer arrival rate(%)	3.9	6.5	2.6	5.2	3.9	6.6	2.5	5.2	6.4	4.8	3.8	3.8
Risk factors Depreciation(%)	2	1.5	2.1	1.2	1.8	2.3	1.4	1.6	2.1	1.9	2.2	2.6
Utility rate Lock in customers $\bar{\boldsymbol{r}}_i$	2.28	2.18	2.5	2.86	2.58	2.46	2.74	2.65	2.5	2.55	2.48	2.41
Added profit rate $\tilde{\boldsymbol{r}}_i$(%)	11	14	12	15	14	16	12	11	15	18	18	15

Amounts of risk factors have been collected in the last year and applied as input to the regression functions. After performing the above measures, final regression model is given below:

Profit =1.2 + 0.25 $\widetilde{f_{\iota,1}}$ + 0.23 $\widetilde{f_{\iota,2}}$ +0.34 $\widetilde{f_{\iota,3}}$ + 0.18 $\widetilde{f_{\iota,4}}$

where $f_{i,1}, \widetilde{f_{\iota,2}}, \widetilde{f_{\iota,3}}, \widetilde{f_{\iota,4}}$ are risk factor of inflation, exit rate of customers, entry rate of customer and depreciation, respectively. Among the factors the entry rate of customers have greater amount which indicates that compared to other properties have a greater impact on the profit and the higher is the rate of arrival of our customers, the greater benefit can be achieved.

This model can be used as a tool to predict profits in future periods and company managers can forecast profits for the next year. Some of the advantages of the proposed model are earning more profit, increasing corporate value and avoiding price volatility.

5 DISCUSSION AND CONCLUSIONS

An enterprise should be able to pricing its products in a way to achieve more earnings proportional to the value provided to the customer and so would maintain its position to the customers, complementary products, competitors and potential newcomers. Pricing is a significant decision for producers (sellers) and has become a difficult issue on the market today that is changing rapidly over time. In this study, we proposed a model under decision support system to help business corporations. In products pricing and history-based pricing method which is used to determine the price of products, a new paradigm for pricing under risk in a business intelligence mechanism was implemented to maximize revenue and fulfill customer demands and their satisfaction. Also the multifactor risk pricing models to predict profits in future periods was used which could identify the importance of each risk factors on products profit. We proceed to interpret the main results of history-based pricing for Business Corporation and express limitations of our work and directions for future research.

5.1 MAIN RESULTS AND INTERPRETATION

With history-based pricing, the average price ($\bar{p}^{HBP}$) is

(a) decreasing as a function of the customer entry rate β

(b) increasing as a function of the customer exit rate δ.

(c) increasing as a function of the firms' time discount rate ρ^f.

Assuming a constant target price for lock in customers (P^{L_*}), by falling prices for new customers (P^{N_*}) Average price ($\bar{p}^{HBP}$) decreases and vice versa.

For more weighted index that P^{N_*} has in equation. The effect of P^{N_*} to calculate the average price is much more than P^{L_*} and the average price is closer to P^{N_*} .

Assuming a constant discount rate and exit rate, with increasing utility rate the price for new customers decreases and vice versa.

Assuming a constant utility rate for new customers, whatever the total rate of exit rate and discount rate is more, target price for new customers increases, and vice versa.

According to above results, average prices fall with an influx of new customers into the market (higher β) since a larger proportion of the consumers are offered introductory discounts. This is the investment effect. With an increased effective discount rate, due to either a higher exit rate of existing customers (higher δ) or firms operating with a higher discount rate ρ^f, this investment effect is weakened.

5.2 FUTURE RESEARCH

In future research web mining exploration techniques such as correlation rules to collect data can be used. Also the effect of specific features on corporate income and profits can be explored. Identifying effective risk factors on profit can be considered in order to provide more accurate model for predicting profit.

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