JURNAL ILMIAH TEKNIK INDUSTRI

ISSN: 1412-6869 (Print), ISSN: 2460-4038 (Online) Journal homepage: <u>http://journals.ums.ac.id/index.php/jiti/index</u> doi:10.23917/jiti.v20i1.13312

Preference-Based Revenue Optimization for App-Based Lifestyle Membership Plans

Fransiscus Rian Pratikto^{1a}, Gerardus Daniel Julianto^{1b}, Sani Susanto^{1c}

Abstract. The demand for a product is rooted in the consumers' needs and preferences. Therefore, a pricing optimization model will be more valid if the demand function is represented under this basic notion. A preferencebased revenue optimization model for an app-based lifestyle membership program is developed and solved in this research. The model considers competitor products and cannibalization effect from products in other fare-class, where both are incorporated using a preference-based demand function. The demand function was derived through a randomized first choice simulation that converts individual utility values into personal choices based on the random parameter logit model. Cannibalizing products are considered as competing products in the simulation scenario. In the pricing optimization, two and three fare classes based on the membership period are considered. The corresponding pricing optimization problem is a mixed-integer nonlinear programming problem with a solution-dependent objective function. Using enumeration, the three-fare-class optimal prices of Rp420,000, Rp300,000, and Rp60,000 for 12-month, 6-month, and 1-month membership, respectively, are better than those of the two-fare-class. Under this policy, the estimated total revenue is Rp30.56 billion, 41.74% greater than that of the current condition.

Keywords: pricing optimization; app-based lifestyle membership; preference-based demand function; randomized first choice; random parameter logit.

I. INTRODUCTION

Price differentiation is the main tactic of revenue management (RM) that aims to exploit differences in willingness-to-pay (WTP) among consumers. In the second-degree and thirddegree price differentiation, fare classes and the corresponding optimal prices are determined to maximize total contribution or total revenue. The problem becomes more complicated when cannibalization and arbitrage are in effect, and the capacity is limited.

The most important input in pricing optimization is the price-response, or demand function, representing the quantity demanded at different price levels. In practice, the choice of demand function affects the complexity of the

- ^b email: gerardus.daniell@gmail.com
- ^c email: sjrhsjrh@gmail.com
- corresponding author

Submited: 13-01-2021 Revised: 24-03-2021 Accepted: 05-06-2021 pricing optimization problem. The demand for a product is rooted in the consumers' needs and preferences. Therefore, a pricing optimization model will be more valid if the demand function is represented under this basic notion. This research aims to develop a pricing optimization model that maximizes total revenue and incorporates consumers' preferences in the demand function.

Most of the previous research in pricing and capacity optimization assumes an independent demand model. Under this assumption, demand is considered exogenous and not affected by sellers' decisions on price, product attributes, and availability. This is only valid for commodities in a competitive market, which are rarely found in the real world. Meanwhile, using an independent demand model in the pricing optimization of a differentiated product in a monopolistic competition market may produce a suboptimal result.

In a multi-fare environment, establishing fences between fare classes is even more difficult, which results in consumers' buy-ups, buy-downs, and diversions (Vulcano, Van Ryzin, & Chaar, 2010). Early research tried to modify the existing independent-demand-based model to cope with these problems. Another study incorporates these

¹ Industrial Engineering Department, Faculty of Industrial Technology, Parahyangan Catholic University, Jln. Ciumbuleuit No. 94, Bandung 40141, Indonesia

^a email: frianp@unpar.ac.id

phenomena in aggregate terms by modeling demand for a product as a function of price and other attributes of the product of interest and competing products (Haynes et al., 2014, Pancras et al., 2012).

Other demand models try to incorporate the impact of the seller's price and availability decision on the quantity demanded in the socalled choice-based revenue management. In this model, consumers' responses to the seller's price and availability decision are incorporated into the demand function. This approach usually assumes a particular behavioral choice model, like the multinomial logit. A general approach for a single-resource multi-fare problem has been developed (Talluri & Van Ryzin, 2004). In this model, the price levels are predetermined, and the corresponding probability distributions of the demand are estimated. A likelihood function that incorporates customer arrival and product choice probability is developed for each price level. The model parameters are calculated using the expectation-maximization algorithm. This work was extended by other researchers who cover other demand models like those based on the Markov chain (Feldman & Topaloglu, 2017) and other types of problems such as assortment (Berbeglia & Joret, 2020) and network problems (Gallego et al., 2015).

While the theory about discrete choice has been developed since the late 1970s, and revenue management initiative was pioneered not long after that, it was not until 2004 that the choicebased demand model was incorporated into revenue optimization. In their seminal work in 2004, Talluri and van Ryzin develop a pricing optimization model for a dynamic single-resource multi-fare problem where the demand is represented using the multinomial logit choice model (Talluri & Van Ryzin, 2004). The price levels are predetermined as in other choice models, and the corresponding probability distribution of demand at each price level is estimated. A likelihood function that incorporates consumer arrival and product choice probability is developed for each price level. The model parameters are estimated from revealedpreference data using the expectationmaximization method. The corresponding solution was found to be in the form of nestedby-fare order. The general discrete choice demand model was incorporated into the revenue-ordered assortment strategy (Berbeglia & Joret, 2020).

Other researchers (Ferguson et al., 2012) extended the work of Talluri and van Ryzin by generalizing the multinomial logit demand model into one that excludes the alternative-specific constant in which the solution cannot be obtained by setting the utility of no-purchase to zero. Another research developed an optimization model for a single-resource problem where the demand follows the Markov modulated demand process (Özkan et al., 2015). While the usual choice-based demand model explicitly represents the demand as a function of products' characteristics, the Markov modulated model considers the external factors that may affect the demand. The corresponding optimization problem was represented using stochastic dynamic programming.

Several types of choice models are commonly used in revenue management (Strauss et al., 2018), they are (1) parametric model like multinomial logit, mixed-multinomial logit, nested logit, Markov chain, and exponential; (2) nonparametric model; and (3) multi-stage choice model. Multinomial logit is probably the most prevalent behavioral choice model due to its mathematical simplicity and relatively high accuracy. Despite its popularity, there are two issues regarding the use of this special type of basic attraction model in representing demand in a revenue optimization problem. The first issue is the tendency to overestimate the market. The second issue is the exponential number of variables when the optimization problem is discrete-choice represented using the deterministic linear programming, a commonly used method to solve the network availability control problem. To overcome this, a flexible and more general attraction model was developed, and the so-called sales-based linear program was used to avoid the exponential number of variables in the optimization problem (Gallego et al., 2015).

In other development, revenue а optimization model was set with the Markov chain demand model (Feldman & Topaloglu, 2017). In this model, customer arrival follows a stochastic process, and the probability of choosing a particular product in the choice set is represented using a discrete-time Markov chain. The model was developed for three types of optimization problems, i.e., assortment and single-resource problems solved using linear programming and network problem solving using reduced linear programming.

The model developed by Talluri and van Ryzin (Talluri & Van Ryzin, 2004) and others that follow are at an aggregate level. The parameters of the choice-based demand model are estimated for the whole population. A disaggregate choice model like the random parameter logit is generally better since it captures the heterogeneity among individuals or between groups. Another development in the theory of discrete choice estimates the model parameters at a group or individual level by using the latent class as implemented in the previous research (Dillingham et al., 2018; Goossens et al., 2014) and hierarchical Bayes (Antonio et al., 2018; Mohammadi, 2020).

In general, revenue optimization with a behavioral choice demand model is more realistic than those with independent demand models since it considers the impact of sellers' decisions and external factors on the quantity demanded. This advantage comes at the expense of simplicity in modeling the optimization problem and obtaining the corresponding solution. Another problem is regarding the continuousness of the decision variable, i.e., price. As in other discrete choice models, the implementation of this model in revenue optimization uses predetermined discrete levels of cost and other product attributes. Usually, the number of levels is not as significant that the variable can be considered continuous. This may limit the search for the optimal solution if the problem is to determine the optimal price in each fare class.

In this research, a model to solve the pricing optimization model in an uncapacitated situation that considers the interdependence between demand and pricing decisions is developed. Instead of using revealed-choice data as in the previous research, the model uses statedpreference choice data. While revealed-choice data are more valid since they come from observed behavior, they cannot analyze nonexistent behavior. This feature is desirable in problems like pricing. A demand model based on stated-preference choice data, although less valid, can be used to evaluate a hypothetical situation that is likely to happen.

The interdependence between demand and pricing decisions is accommodated using a preference-based demand model. It is preference-based because it is derived from individual utility values, representing how much each level of product attribute (including price) is worth each respondent. Using these utility values as input, we can predict how each respondent would choose a particular competitive scenario. By aggregating the choices across all individuals and multiplying them with the achievable market size, the quantity demanded at any given price can be estimated. In this demand model, the quantity demanded of a product is not a function of its price only but also its competitors' prices. Competitors' prices are incorporated into the competitive scenario out of which the respondents would make their choices. Since the utility values are estimated at the individual level, customer heterogeneity is incorporated in the demand function.

The model is implemented in a case study of the pricing for an application-based lifestyle membership plan. App-based lifestvle membership plans are membership plans that offer lifestyle (restaurants, gyms, sports, beauty deals through a treatment, etc.) mobile application. The memberships are usually provided through lifestyle discovery apps, and most of them focus on restaurants. The price differentiation is generally time-based, and the optimization problem is not capacitated.

The novelty of this research is the use of preference-based demand function in pricing optimization. Since competitors' prices are considered in deriving the demand function, the cannibalization effect of products in other fareclass can be estimated by treating them as competitors. The multi-fare problem can be analyzed more realistically, and hence the corresponding optimal prices are more valid. This advantage comes at the expense of the simplicity of the optimization problem. Due to its complexity, the solution to the pricing problem was obtained using enumeration, which combines simulation and optimization.

II. RESEARCH METHOD

Almost all previous research on revenue optimization that incorporates choice-based demand models uses an aggregate level of analysis. This means that the model parameters are estimated at the population level. Other models estimate parameters at a disaggregated level like individual or group. In general, a disaggregate model is more realistic since it considers the heterogeneity of the population at a more acceptable level.

In our research, the demand function is based on the behavioral model of random parameter logit, also called the mixed multinomial logit. Unlike the aggregate multinomial logit, the parameters of the mixed multinomial logit are estimated at the individual level. While in the previous research (Talluri & Van Ryzin, 2004). The model's parameters in this research are estimated from stated-preference choice data Bayesian estimation method. Compared to other stated-preference data types (ranking, rating, best-worst), choice data are considered more realistic since it mimics what consumers do in the market. The data is collected using a questionnaire that consists of a set of choice tasks generated randomly out of a set of attributes with predetermined levels. Each choice task usually consists of three to four product concepts, where each concept is a combination of attributes' levels. A "none" option may be added to accommodate the situation where respondents are not interested in any product concepts in the choice task. Each choice task represents a hypothetical choice situation, out of which respondents are asked to pick one product concept that best suits their preferences. Otherwise, they should choose the "none" option. One or two fixed choice tasks are usually added to the questionnaire for internal validation purposes.

а Let $\boldsymbol{\beta}_n = (\beta_{n1}, \dots, \beta_{nB})'$ be vector representing utilities that respondent n obtains from each attribute level. The indices 1, ..., B corresponds to each attribute level and the "none" option (if any). Let $\boldsymbol{\beta} = (\boldsymbol{\beta}_1', ..., \boldsymbol{\beta}_N')$ be a matrix representing utilities of all respondents (there are N respondents). In the hierarchical Bayes estimation method, individual-level utilities are assumed to follow a multivariate normal distribution such that $\beta_n \sim N(\mu, \Sigma)$, where μ is the mean vector and Σ is the covariance matrix (Antonio et al., 2018; Mohammadi et al., 2020).

Classical estimation methods for choice data involve maximizing some likelihood function, either using observed or simulated probabilities. estimation methods These produce the parameters of the distribution of utility values in an aggregate term. Using aggregate utility values is like using mean and variance to represent the population. Having utility values for each respondent is always better than just the average value of the population. However, this approach has two drawbacks, i.e., difficulty in maximizing the likelihood function of certain behavioral models and consistency and efficiency problems in the estimation process (Train, 2009).

The Bayesian estimation considers the probability distribution of the parameters as a posterior distribution, updated using incoming observations given the priors. The estimation is conducted iteratively using the Markov chain Monte Carlo method. Hierarchical Bayes is considered the best method that falls into this category. Hierarchical Bayes is based on the Bernstein-von Mises theorem, which simply states that the posterior probability distribution of a stochastic variable is asymptotically independent of the prior as the sample size increases. Using this notion, the stochastic parameters of the utility model $\beta_n \sim N(\mu, \Sigma)$ can be estimated iteratively, where each is conditional on the other two. For statistical convenience, μ is assumed to be normally distributed, while Σ follows an inverted Wishart distribution. Under this assumption, the estimate of μ conditional on Σ and β follows a multivariate normal distribution.

In contrast, the estimate of Σ conditional on μ and β follows an inverted Wishart distribution. In each iteration, the estimation of β is conducted using the Gibbs sampling conditional on μ and Σ from the previous iteration. The cycle is repeated until the values of those parameters converge and enough to be systematically sampled to obtain independent observations. A comprehensive discussion of this algorithm can be found in (Train 2009).

Suppose in our discrete choice experiment we define A attributes labeled as attribute 1, ..., A, each has $b_1, ..., b_A$ levels, such that there is a total of $B = \sum_{a=1}^{A} b_a$ levels. For product *i*, we define $\mathbf{x}_i = [x_{p_i}, \mathbf{x}_{q_i}, x_0]$ as a binary vector of length B +1 such that x_{p_i} corresponds to the price level of product *i*. In contrast, $\mathbf{x}_{\mathbf{q}_i}$ corresponds to other levels, including price levels different than x_{p_i} , the levels of non-price attributes, and x_0 corresponds to the "none" option. Now let $\boldsymbol{\beta}_n$ be a vector of length B + 1 representing utilities of each attribute's levels and the "none" option for respondent *n*. The order of elements in $\boldsymbol{\beta}_n$ follows those in \mathbf{x}_i .

Given the individual utility value of each attribute level, several methods can be used to predict and aggregate individual choices in a particular choice situation; they are the first choice, logit, and randomized first choice. The randomized first choice is considered the best (Huber et al., 2007). This is because the randomized first choice is immune from the independence-of-irrelevant-alternatives problem and more realistic since it incorporates randomness in modeling how people choose.

Under the randomized first choice model, the total utility of product i for individual n, denoted by (U_{ni}) , can be determined by drawing from

$$U_{ni} = \mathbf{x}_{i}'[\boldsymbol{\beta}_{n} + \boldsymbol{\varepsilon}_{n}] + \varepsilon_{i}$$

= $\left[x_{p_{i'}} \mathbf{x}_{\mathbf{q}_{i'}} x_{0}\right]' [\boldsymbol{\beta}_{n} + \boldsymbol{\varepsilon}_{n}] + \varepsilon_{i}$ 1)

There are two random elements added to incorporate respondents' inconsistency in making the choice decision. The first one is ϵ_n which

represents the inconsistency of respondent n in evaluating how much an attribute level is worth. The second one is ε_i which incorporates error in how respondents evaluate product i in the choice set. Once the values of ε_n and ε_i have been drawn, respondent n will choose product i out of choice set S if $U_{ni} \ge U_{nj}$ for all $j \ne i$, and $i, j \in S$. It is obvious that this choice does not only depend on the price (p_i) but also on the non-price attributes (\mathbf{q}_i) and the "none" option (x_0) . It is also conditional on the alternatives available in the market, which are represented by the price

PJ and non-price attribute vector \mathbf{q}_j for all $j \neq i$. Hence, the share-of-preference can be obtained by aggregating choices across all respondents

$$s_i(p_i | \mathbf{q}_i, x_0, \mathbf{p}_j, \mathbf{q}_j \forall j \neq i) = \frac{\sum_{n=1}^{N} \mathbf{1}_{U_{ni} \geq U_{nj}}}{N} 2)$$

where U_{ni} and U_{nj} refer to Equation (1).

By drawing a sufficiently large sample of U_{ni} and discard the transient samples, the mean share-of-preference of product *i*, denoted by $\bar{s}_i(p_i|\mathbf{q}_i, x_0, P], \mathbf{q}_j \forall j \neq i)$, can be estimated. If the mean share-of-preference is considered as market share for fare-class *i*, demand for fareclass *i* at the price of p_i can be estimated as follows

$$d_i(p_i) = D\bar{s}_i(p_i | \mathbf{q}_i, x_0, \mathbf{p}_j, \mathbf{q}_j \forall j \neq i)$$
3)

where D is the maximum achievable market size.

By simulating for all price levels (usually five or six), several price-proportion data pairs $[p_i, d_i(p_i)]$ are obtained. These data pairs can be used to derive a continuous and differentiable demand function using curve-fitting or interpolation. Curve-fitting can be done by assuming a particular demand function (Huang et al., 2013). Meanwhile, to get a better fit, the cubic spline interpolation (Abdul Karim, 2018) is used in this research. After interpolating the $[p_i, d_i(p_i)]$ data pairs, now we can consider $d_i(p_i)$ as a continuous function of p_{i_i} \mathbf{q}_{i_j} PJ, and \mathbf{q}_i .

Since the model focuses on determining the prices of the product of interest, the levels of the price and other attributes of the competitors' products are assumed to be fixed. Hence, the indices that correspond to the competitors'

products can be removed from the problem formulation.

Suppose there are K products denoted by $\{1, ..., K\}$, each serving a different fare-class, and together they compete with competitors' products. Those K products are cannibalizing each other. Since the problem is not capacitated, the model aims to determine the optimal price for each fare-class without capacity allocation. In a more general model, K can be considered as the decision variable. Fare-class 1 is associated with the product with the highest price, while fare-class K is the lowest.

Based on the way the demand function is derived as described above, the demand in a particular fare-class depends not only on the price of the product in that fare class but also on those in other fare-classes. Hence, the demand in fare-class k at the price of p_k can be expressed as $d_k(p_k) = D\bar{s}_k(p_k|p_l, \forall l \neq k)$

4)

where $k, l \in \{1, ..., K\}$. Since incremental costs in our problem are practically zero, the model seeks to maximize the total revenue

$$\max_{p_1,\dots,p_K} \sum_{k=1}^K d_k(p_k) \cdot p_k$$
 5)

By the definition of the fare-class, $0 \le p_I \le$

 $p_2 \leq \cdots \leq p_K$. Considering Equation (4) as the constraint to attaining the objective function in Equation (5), the optimization problem has objective function coefficients that depend on the values of the decision variables.

Since the demand function is obtained using the cubic splines interpolation, the objective function is a quartic polynomial. This adds complexity to the optimization problem. According to (Ahmadi et al., 2013), determining the convexity of such problems is NP-hard. In this research, the decision variables are discretized, and the solution is obtained using enumeration.

III. RESULT AND DISCUSSION

In this research, six attributes were defined in the discrete choice experiment questionnaire design. The attributes were determined using the critical incident technique implemented in previous research (Cunningham et al., 2020). Ten current users were interviewed, and their best and worst experiences with the product were revealed. 5-10 critical incidents were obtained from each respondent, which was subsequently analyzed and categorized and resulted in six attributes, i.e., merchant variation, brand, promotion, membership period, number of vouchers, and price. The results were validated using data from

Table 1. Attributes and leve	els
------------------------------	-----

Attributes	Levels
1. Brand	1. Brand A
	2. Brand B
2. Promotion	1. Buy one get one for food
	2. Buy one get one for food and 50% off for lifestyle
	3. Buy one get one for food and buy two get two for drinks
3. Merchant variation	1. More fine-dining restaurants (with picture)
	2. More casual restaurants (with picture)
4. Membership period	1. 1 month
	2. 6 months
	3. 12 months
	4. No expiry
5. Number of vouchers	1. 3 vouchers
	2. 10 vouchers
	3. Unlimited
6. Price	1. Rp50,000
	2. Rp200,000
	3. Rp350,000
	4. Rp400,000
	5. Rp500,000

two additional respondents, and since there is no new attribute obtained from these data, those six attributes are valid. The attributes and corresponding levels are depicted in Table 1.

The levels of the non-price attributes were determined based on those that were available in the market. To determine the price levels, a small survey was conducted to reveal the price levels considered reasonable by the customers.

In a discrete choice experiment, a product is defined as a combination of attribute levels. To prevent unrealistic combinations like one with high-quality attributes and a low price, some prohibitions in the design of our choice set were set, as seen in Table 2. Prohibitions should be set carefully. Too few prohibitions may cause unrealistic product concepts, while too many will affect the accuracy of the utility estimates.

Table	2.	Prohibited	pairs
		11011101100	pans

1 st Attribute-Level	2 nd Attribute-Level
Attribute 5 level 2	Attribute 6 level 1
Attribute 5 level 3	Attribute 6 level 1
Attribute 5 level 3	Attribute 6 level 2
Attribute 1 level 2	Attribute 2 level 2
Attribute 4 level 4	Attribute 5 level 3
Attribute 4 level 1	Attribute 6 level 4
Attribute 4 level 1	Attribute 6 level 5
Attribute 4 level 2	Attribute 6 level 1
Attribute 4 level 2	Attribute 6 level 4
Attribute 4 level 2	Attribute 6 level 5
Attribute 4 level 3	Attribute 6 level 1

discrete choice Īn а experiment questionnaire, each respondent's set of choice tasks are randomly generated that there would not be two or more respondents that receive the same set of choice tasks. As in other experiments, randomization is a critical aspect of the discrete choice experiment to obtain unbiased results. With attributes' level configuration as in Table 1, a respondent needs to evaluate 2×3×2×4×3×5=720 product concepts in a full factorial experiment. Asking a respondent to do that would be impractical, if not impossible.

In this research, there are six random choice tasks in each questionnaire, and each has three products and a "none" option. Each respondent needs to evaluate 18 product concepts. As in other fractional factorial experiments, these 18 concepts should be randomly chosen out of 720 for each respondent. Another requirement is that the number of levels in each respondent's choice sets must be balanced, which refers to the number of occurrences of each level in the choice task set of a particular respondent.

Usually, the recommended number of choice tasks in a questionnaire is 12-18 without affecting the data quality. Still, our experience suggested that without any incentive, answering 12 choice tasks of the same structure may cause boredom which eventually affects the data quality. One fixed task is added to each questionnaire for validation purposes. Figure 1 depicts an example



Figure 1. Example of the choice task

of a choice task in our questionnaire. The name of the brand is replaced for confidentiality purposes.

Based on the location of the tenants covered in the membership plans, the survey population is people living in the greater area of Jakarta. An online survey was conducted, and 300 completed questionnaires were collected. This is the minimal sample size required for this research (Orme & Chrzan, 2017).

Using these choice data, individual-level

utilities were estimated using the hierarchical Bayes method. A typical output of the estimation from a particular respondent is presented in Table 3. The values in Table 3 are in interval scale and zero-centered. Hence, they can only be compared within the same attributes, not between different attributes. A more excellent utility value refers to a preferred level.

Individual-level utility values are the main ingredient needed to predict one's choices in any choice scenario constructed using levels in Table 1. These are the input to Equation 1, which then produces the share of preference for each product concept calculated using Equation 2.

Attributes	Level	Utilities
Brand	Brand 1	0.253
	Brand 2	-0.253
Promo	Buy 1 Get 1 (Food)	0.222
	Buy 1 Get 1 (Food) &	
	50% Off (Lifestyle)	-0.430
	Buy 1 Get 1 (Food) &	
	Buy 2 Get 2 (Drinks)	0.207
Merchant	More fine-dining	
	restaurants	0.959
	More casual	
	restaurants	-0.959
Period	1 month	-1.258
	6 months	-0.914
	12 months	0.572
	No Expiry Date	1.600
# of vouchers	3 vouchers	-1.136
	10 vouchers	0.353
	Unlimited	0.783
Price	Rp50,000	0.723
	Rp200,000	0.175
	Rp350,000	-0.305
	Rp400,000	-0.484
	Rp500,000	-0.677
	None	-4.015

Table 3. Utility values of respondent #6

Internal validation on the estimation result was conducted by comparing the actual share of preference on the fixed choice task based on the survey data with those estimated using the individual level utility values obtained from the hierarchical Bayes estimation. The mean absolute error is 2.75% which is a good result despite the relatively small sample size.

The Lighthouse Studio 9.6.1 from Sawtooth Software was used to design and generate the questionnaires, administer the online survey, and estimate the utilities.

In this research, the product of interest is Brand 1, for which, based on the interview with the product owner, two scenarios were considered: (1) two fare-classes and (2) three fareclasses. In the first scenario, 1-month and 12month memberships are offered, while in the second scenario, there is an additional membership of 6-month.

The optimization problem of the first scenario becomes

$$\max_{p_1, p_2} d_1(p_1) p_1 + d_2(p_2) p_2$$
6)

s/t

$$d_{1}(p_{1}) = D\bar{s}_{1}(p_{1}|p_{2})$$

$$d_{2}(p_{2}) = D\bar{s}_{2}(p_{2}|p_{1})$$
7)

8)

with a nonnegativity constraint $p_1, p_2 \ge 0$, and $p_1 > p_2$.

Meanwhile, the optimization problem of the second scenario becomes

$$\max_{p_1, p_2, p_3} d_1(p_1)p_1 + d_2(p_2)p_2 + d_3(p_3)p_3$$
9)

 $d_1(p_1) = D\bar{s}_1(p_1|p_2,p_3)$

$$d_2(p_2) = D\bar{s}_2(p_2|p_1, p_3)$$
10)

$$DS_2(p_2|p_1, p_3)$$
 11)

$$d_3(p_3) = D\bar{s}_3(p_3|p_1, p_1)$$
12)

with a nonnegativity constraint $p_1, p_2, p_3 \ge 0$, and $p_1 > p_2 > p_3$.

Since this problem is almost impossible to be solved analytically, enumeration was used to obtain the solution. To make enumeration possible, the decision variables need to be discretized. Based on the discussion with the product owner, the price in each fare class is restricted to be a multiple of Rp10.000. With this constraint, the solution space of the decision variables (p_1, p_2) consists of (51,000, 50,000), (52,000, 50,000), (52,000, 51,000), ..., (500,000, 490,00) in the first scenario. In the second scenario, the solution space consists of (52,000, 51,000, 50,000), (53,000, 51,000, 50,000), (53,000, 52,000, 50,000), ..., (500,000, 490,000, 480,000).

The utility values of the price levels are only available for those defined in Table 1. Evaluating other price levels requires us to estimate the utility of those levels. The cubic spline interpolation is used to do that, and then the enumeration proceeds accordingly.

The enumeration for a particular solution point $(p_1^{(s)}, p_2^{(s)})$ in the first scenario proceeds as follows:

- 0. Set $p_1 = p_1^{(s)}$ and $p_2 = p_2^{(s)}$
- 1. Estimate \bar{s}_1 using the randomized first choice simulation by setting $p_2 = p_2^{(s)}$
- 2. Estimate \bar{s}_2 using the randomized first choice simulation by setting $p_1 = p_1^{(s)}$
- 3. Calculate $d_1(p_1^{(s)})$, $d_2(p_2^{(s)})$, and the corresponding total revenue

Accordingly, in the second scenario the enumeration for a particular solution point $(p_1^{(s)}, p_2^{(s)}, p_3^{(s)})$ proceed as follows:

0. Set $p_1 = p_1^{(s)}$, $p_2 = p_2^{(s)}$, and $p_3 = p_3^{(s)}$

- 1. Estimate \bar{s}_1 using the randomized first choice simulation by setting $p_2 = p_2^{(s)}$ and $p_3 = p_3^{(s)}$
- 2. Estimate \bar{s}_2 using the randomized first choice simulation by setting $p_1 = p_1^{(s)}$ and $p_3 = p_3^{(s)}$
- 3. Estimate \bar{s}_3 using the randomized first choice simulation by setting $p_1 = p_1^{(s)}$ and $p_2 = p_2^{(s)}$
- 4. Calculate $d_1(p_1^{(s)})$, $d_2(p_2^{(s)})$, $d_3(p_3^{(s)})$, and the corresponding total revenue

The randomized first choice simulations in

T	ab	le	4.	0	ptimal	solu	itions
-				_			

alue of the			
objective			
function			
Dp28.80 billior			
1p20.09 billion			
Rp30.56 bilion			
Kp30.56 billor			

each enumeration make the computation quite lengthy. Under the first scenario, there are 990 solution points to be evaluated, while the second scenario has 2000. Using HP laptop 14s-cf2xxx with Intel(R) Core(TM) i7-10510U CPU @1.80GHz 2.30GHz and 16GB RAM, the computation took about 6 hours for the first scenario and about 12 hours for the second one. The results are presented in Table 4.

It is evident in Table 4 that price differentiation with three fare-classes produces more significant total revenue than one with two fare-classes. To assess the quality of this solution, the result was compared with the current condition. Since we do not have access to the sales data, we use the randomized first choice simulator to estimate the current condition. The simulation scenario was set to represent the actual competitive situation, as depicted in Table 5. The number in cells of Table 5 refers to the level number in Table 1.

able 5. Current competitive setting	Γá	able	5.	Current	com	petitive	setting	
-------------------------------------	----	------	----	---------	-----	----------	---------	--

	Attri	butes				
Products	Brand	Promotion	Merchant	Period	# of vouchers	Price
11	1	2	1	3	1	Rp400,000
12	1	2	1	2	1	Rp250,000
13	1	2	1	1	1	Rp 50,000
21	2	3	2	3	3	Rp350,000
22	2	3	2	4	2	Rp200,000
23	2	3	2	4	1	Rp 90,000

The simulator was modified to incorporate all price levels in multiple Rp10,000 between Rp50,000 – Rp500,000. For those price levels, the utility values were estimated based on the utility of the price levels in Table 1 using the cubic spline interpolation.

Simulating the scenario in Table 5, it was found that the shares of preference are 4.6%, 2.2%, and 16.0% for products 11, 12, and 13, respectively, with estimated total revenue of Rp21.56 billion. Hence, implementing the optimal solution in Table 4 will result in an estimated 41.74% increase in total revenue compared to the current condition.

Without cannibalization, price differentiation with more fare classes always results in more significant total revenue. When cannibalization is in effect, this is not always the case because people with higher willingness-to-pay may buy lower-priced products. This research uses the method the demand function is derived. This cannibalization effect has been considered. Table 4 is valid not only because it takes the individual preference variability into account but also considers the cannibalization effect between fare classes. These are two important features that need to be looked into in multiple fare-class pricing optimization (Vulcano, Van Ryzin, & Chaar, 2010).

In the general choice-based revenue management model, the fare classes are predetermined, and the decision variable is whether a particular fare class will be open or not. The probability distribution of the demand in each fare class is estimated using revealedpreference data on an aggregate basis.

Generally, a disaggregate model of preferences as used in this research is better than the aggregate one. This research shows that this advantage comes at the expense of the simplicity of the pricing optimization problem. The solution to the discretized model was obtained by enumerating all points in the solution space, within which the randomized first choice simulation was invoked to estimate the model's parameters. This complex mechanism has caused the computation time to become guite lengthy. In problems with a more significant number of fare classes, the computation time will increase due to the exponential increase in the number of solution points.

Another trade-off is regarding the use of the stated-preference data, which can estimate choices in a hypothetical scenario but may produce overstated demand (Koetse, 2017). The trade-off between these two approaches reveals the opportunity to develop a hybrid method that combines the advantages of both. One possibility is a model with individual-level parameters which dynamically updated using revealed-preference data. Another possible extension of the model is incorporating the number of fare-class as the decision variable. This makes the model more general but, at the same time, increases the complexity of obtaining the solution.

IV. CONCLUSION

A preference-based revenue optimization model for an app-based lifestyle membership program is developed and solved in this research. Using a preference-based demand function, the model considers competitor products and the cannibalization effect from products in other fareclass. The demand function was derived through the randomized first choice simulation, which converts individual utility values into estimated shares of preference based on the random parameter logit model. Cannibalizing products are considered as competing products in the simulation scenario. Two scenarios were considered in the pricing optimization, one with two and one with three fare classes. Both are based on the membership period. The corresponding pricing optimization problem is a mixed-integer nonlinear programming problem with a solution-dependent objective function. We found that the three-fare-class optimal prices of Rp420,000, Rp300,000, and Rp60,000 for 12month, 6-month, and 1-month membership, respectively, are better than those of the twofare-class. Under this policy, the estimated total revenue is Rp30.56 billion, more than 41% greater than that of the current condition.

Future research can be directed towards developing a more general model where the number of fare-class becomes a decision variable and exploring more efficient methods for obtaining the solution.

References

- Abdul Karim, S. A. (2018). "Construction new rational cubic spline with application in shape preservations." *Cogent Engineering, 5*(1).
- Ahmadi, A. A.; Olshevsky, A.; Parrilo, P. A.; Tsitsiklis, J. N. (2013). "NP-hardness of deciding convexity of quartic polynomials and related problems." *Mathematical Programming*, 137(1–2), 453–476.

- Antonio, A.L.M., Weiss, R.E., Saigal, C.S., Dahan, E., Crespi, C.M. (2018). "A Bayesian hierarchical model for discrete choice data in health care." *Statistical Methods in Medical Research*, *27*(12), 3544–3559.
- Birbiglia, G.; Joret, G. (2020). "Assortment Optimisation Under a General Discrete Choice Model: A Tight Analysis of Revenue-Ordered Assortments." *Algorithmica, 82* (4), 681–720.
- Cunningham, U.; De Brún, A.; McAuliffe, E. (2020). "Application of the critical incident technique in refining a realist initial programme theory." *BMC Medical Research Methodology*, *20*(1), 131.
- Dillingham, R.T.; Breffle, W.S.; Kelly, M.C. (2018). "A latent-class discrete-choice model of demand for economics electives: a case study on the challenge to increase enrollment." *Journal of Marketing for Higher Education, 28* (1), 113–127.
- Feldman, J.B., Topaloglu, H. (2017). "Revenue Management Under the Markov Chain Choice Model." *Operations Research*, 65(5), 1322–1342.
- Ferguson, M. E.; Garrow, L. A.; Newman, J. P. (2012). "Application of discrete choice models to choicebased revenue management problems: A cautionary note." Journal of Revenue and Pricing Management, 11(5), 536–547.
- Gallego, G.; Ratliff, R.; Shebalov, S. (2015). "A General Attraction Model and Sales-Based Linear Program for Network Revenue Management Under Customer Choice." Operations Research, 63(1), 212– 232.
- Goossens, L. M. A.; Utens, C. M. A.; Smeenk, F. W. J. M.; Donkers, B.; van Schayck, O. C. P.; Rutten-van Mölken, M. P. M. H. (2014). "Should I Stay or Should I Go Home? A Latent Class Analysis of a Discrete Choice Experiment on Hospital-At-Home". Value in Health, 17(5), 588–596.
- Haynes, M.; Thompson, S.; Wright, P. W. (2014). "New Model Introductions, Cannibalization and Market Stealing: Evidence from Shopbot Data." The Manchester School, 82(4), 385–408.
- Huang, J.; Leng, M.; Parlar, M. (2013). "Demand Functions in Decision Modeling: A Comprehensive Survey and Research Directions." Decision Sciences, 44(3), 557–609.
- Huber, J.; Orme, B.; Miller, R. (2007). "Dealing with Product Similarity in Conjoint Simulations." In A. Gustafsson, A. Herrmann, & F. Huber (Eds.), Conjoint Measurement: Methods and Applications (4th ed., pp. 347–362). New York: Springer.
- Koetse, M.J. (2017). "Effects of payment vehicle nonattendance in choice experiments on value estimates and the WTA–WTP disparity." Journal of Environmental Economics and Policy, 6(3), 225–245.

- Mohammadi, T.; Zhang, W.; Sou, J.; Langlois, S.; Munro, S.; Anis, A. H. (2020). "A Hierarchical Bayes Approach to Modeling Heterogeneity in Discrete Choice Experiments: An Application to Public Preferences for Prenatal Screening." The Patient -Patient-Centered Outcomes Research, 13(2), 211– 223.
- Orme, B. K.; Chrzan, K. (2017). "Becoming an Expert in Conjoint Analysis: Choice Modeling for Pros." Orem, UT: Sawtooth Software, Inc.
- Özkan, C.; Karaesmen, F.; Özekici, S. (2015). "A revenue management problem with a choice model of consumer behavior in a random environment." OR Spectrum, 37(2), 457–473.
- Pancras, J.; Sriram, S.; Kumar, V. (2012). "Empirical Investigation of Retail Expansion and Cannibalization in a Dynamic Environment." Management Science, 58(11), 2001–2018.
- Strauss, A. K.; Klein, R.; Steinhardt, C. (2018). "A review of choice-based revenue management: Theory and methods." European Journal of Operational Research, 271(2), 375–387.
- Talluri, K.; Van Ryzin, G. (2004). "Revenue Management Under a General Discrete Choice Model of Consumer Behavior." Management Science, 50(1), 15–33.
- Train, K. E. (2009). "Discrete Choice Methods with Simulation (2nd ed.)". Cheltenham: Edward Elgar.
- Vulcano, G.; Van Ryzin, G.; Chaar, W. (2010). "Choicebased revenue management: An empirical study of estimation and optimization." Manufacturing and Service Operations Management, 12(3), 371–392.